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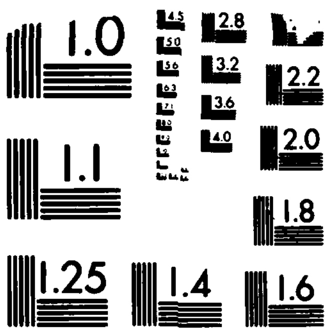

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Final Technical Report
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RELIABILITY MODEL DEMONSTRATION STUDY

Hughes Aircraft Company

J. E. Angus, J. B. Bowen and S. J. VanDenBerg

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This report contains the results of a study to determine the use and applicability to Air Force software acquisition managers of six quantitative software reliability models to a major command, control, communications, and intelligence (C^{3}I) system. The scope of the study included the collection of software error data from an on going C^{3}I project, fitting six software reliability models to the data, analyzing the predictions provided by the models, and developing conclusions, recommendations, and (over)

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guidelines for software acquisition managers pertaining to the use and applicability of the models.

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1. SUMMARY OF STUDY RESULTS

1.1 Introduction

The objective of this study was to demonstrate the use and applicability to Air Force software acquisition managers of six quantitative software reliability models to a major command, control, communications, and intelligence (C^3I) system. The scope of the effort involved the collection of software error data from an ongoing C^3I project, (the Hughes Joint Surveillance System, JSS, was selected), fitting the six models to the data thus collected, analysis of the predictions provided by the models, and the development of conclusions, recommendations, and guidelines for software acquisition managers pertaining to the use and applicability of the six software reliability models.

This research was partially motivated by the recommendations from the Validation of Software Reliability Models study (RADC-TR-79-147) (Schafer, et.al. (1979)). In that study it was determined that the cause of the generally poor fits obtained for the models studied therein could not be conclusively attributed to the failure of the internal assumptions of the models, and that the integrity of the data used was a significant factor whose effect could not be determined. It was recommended that a controlled data collection project be undertaken to assure data integrity and therefore provide better means for evaluating the models.

While a C^3I project does not afford the degree of controllability implicit in the recommendation of the Validation of Software Reliability Models study, every effort was made in this investigation to collect the highest quality data possible without significantally perturbing the JSS project. In cases where the exact data input requirements for a model were not met, we were able to use the models' assumptions to define a version of the model which would accept the data available. In other instances, the manner in which the data was collected was known a-priori to be in violation of a models' assumptions. In these instances, we were able to use supplementary data (such as test phase and compilation unit name) to restrict attention to a class of data in which the assumptions would be roughly satisfied. Overall, every effort was made to improve the fit of each model, without altering data (e.g., "estimating" the times between error detections rather than observing them).

In performing this study, we have tried to formulate guidelines, conclusions, and recommendations based on the results of fitting the models to the JSS data. It is conceivable (although presumably less so on other Hughes C^3I projects) that different conclusions could be obtained from data from a different C^3I project. A wide range (from no success to complete success) of results have been reported in the past by other researchers

for the models studied herein based on different data sources. We are not aware, however, of any past efforts performed on C^3I data as extensive, well controlled, and well documented as the JSS data. Nevertheless, because the software error detection and removal process is so dependent on factors extraneous to the software (e.g. testing intensity, manpower, skill levels, scheduling constraints, etc.) we caution that extrapolation of our conclusions to other projects in other companies may be spurious.

It is hoped that the results of this study will provide assistance to RADC, and other government agencies involved in research and development, in directing their future resources in software reliability modeling. It is also hoped that the data collected in this study can be used by other researchers as a "proving ground" for any new models which may be proposed for future industrial use.

1.2 Data Collection

The primary motivation for collecting software error data is to improve the quality of the delivered system. These data are valuable not only to assess and predict the quality of the software from which they were gathered, but also to provide lessons learned for the next similar project. Often errors are repeated, even with the same programming staff, on similar projects merely because of the complexity of the software and the inability to remember the details of past experience (Gannon, 1983).

It is imperative that both project and data collection personnel be trained in the definition of error classifications, as well as the data collection procedures. This training should take place before software development begins. Automated data collection may be the only means to obtain objective data, but some projects either cannot afford the extra expense or are precluded from utilizing automated schemes because of security restrictions. It is essential that accuracy and consistency of the data be validated early in the project as well as throughout the duration of the project.

The following is a summary of guidelines for the collection of error data from software development projects, for the purpose of providing input data to software reliability models and metrics:

- Early training in classification/collection procedures

- Standard classification and consistent definitions

- Collection should start when software is under configuration control

- Continual monitoring including automatic validation and troubleshooting

- Use of automated procedures for recording, qualification, and reduction

1.3 Models and Usage Guidelines

The six models under investigation in this study were the Geometric Poisson (Moranda, 1975), Nonhomogeneous Poisson (Goel & Okumoto, 1980), Imperfect Debugging (Goel, 1978), Generalized Poisson (Schafer, et.al. 1979), IBM Poisson (Brooks & Motley 1980), and Binomial (Schafer et.al. 1979). In studying these models, many striking similarities with the original Jelinski-Moranda (Moranda, 1975) model and its principles were discovered. In fact, it was found that for purposes of comparison, each model could be reparametrized in terms of parameters which directly relate to the Jelinski-Moranda parameters (namely, N, the initial number of errors, and ϕ, the error detection rate of a single error).

Because of the unavailability of the exact times between error detections, it was necessary to modify the procedure for fitting the Imperfect Debugging Model (Goel, 1978). It is shown in Section 3.2 that if only errors which are actually removed are counted in the process, then the Imperfect Debugging model reduces to the original Jelinski-Moranda model. Based on this observation, a version of the Jelinski-Moranda model designed for frequency data proposed by Lipow (1974) and further developed by Schafer et.al. (1979) is used in place of the Imperfect Debugging model.

Another model which required modification was the Geometric Poisson Model (Moranda, 1975). The modification required was to allow unequal time interval lengths in the input data. This modification was straight-forward, and made entirely within the assumptions of the original equal time interval model.

The final model which was modified was the IBM Poisson. Although this modification was not strictly necessary, it was made because we felt it would improve the model's fit. The original version was also fitted, in addition to the modified version. The modified IBM model is discussed in Section 3.4.

The results of fitting the models are given in Section 4. The procedure used to fit the models was to estimate the models' unknown parameters using the techniques advocated by their respective authors (usually a pseudo maximum likelihood or pseudo least squares principle). A chi-square goodness-of-fit test was then performed whenever valid parameter estimates were obtained. The data selected for fitting the models was chosen from single compilation units (CUs) and test phases to eliminate the effects (which are counter to the assumptions made by the models) of software build-up and variability, and varying test intensity.

In general, the models performed poorly with respect to fit. Each model experienced problems with lack of convergence in its parameter estimation algorithms. Nevertheless, the results were considerably better than those achieved in the Validation of Software Reliability Models study (Schafer, et.al. 1979) with the best fitting model overall being the modified version of the IBM Poisson model with 53% of its attempts leading to a good fit (i.e. a good fit means that the chi-square goodness-of-fit test was not failed at the 0.05 level of significance). A summary of the results is given in Table 1.3.1.

A measure, derivable from the outputs of any of the six models studied herein, which would be of use in monitoring formal and qualification testing of software, is introduced in Section 3.11. This measure is the residual number of errors in the software. In comparing this measure as provided by the software reliability models studied herein with the actual performance history of the JSS project, an important observation can be made. First, the models (when they fit) provide little information concerning the number of errors in future test phases. That is, estimates of residual errors based on current data are inconsistent with the number of errors subsequently detected and removed in the next test phase. We believe that this is best explained not only by possible inadequacies in the models, but mostly by the fact that each test phase can expose only its own class of errors, and some of these errors may be uniquely detectable by that test phase and no other.

Table 1.3.1

Summary of Model Fitting Results

Model	% fit	% no fit	% lack of convergence
Modified IBM Poisson	53	22	25
Nonhomogeneous Poisson	33	25	42
Geometric Poisson	33	25	42
Generalized Poisson	35	10	55
Binomial	27	16	57
Jelinski-Moranda	18	8	74
IBM Poisson	0	0	100

While the general recommendation concerning the models studied herein is that they not be adopted for general or contractual use either by acquisition managers or software project managers, some guidelines can be followed which will aid in their use. These guidelines are:

a) Collect error data according to the guidelines for data collection in Sections 1.2 and 2.4.

b) Apply the models at the compilation unit level.

c) Apply the models to data within a single test phase.

d) Interpret the results in the context of that test phase only, and use the results to decide if more testing within that phase is necessary.

e) Do not use the results of a model if, in fitting the model, it fails the chi-square goodness-of-fit test at an appropriate level of significance (we recommend 0.05).

2. DATA COLLECTION

In compliance with the statement of work, Hughes utilized a C^3I software development project under the control of ESD for the demonstration of the applicability of software reliability prediction models. Hughes selected the Joint Surveillance System (JSS) which qualified with respect to the following characteristics: 1) development IAW AF 800-14, Volume II; 2) use of high order programming language IAW DODI 5000.31; 3) an estimated size of at least 20,000 DSLOC excluding comments; and 4) a development schedule compatible with the demonstration study schedule. The following paragraphs describe JSS project characteristics, emphasize lessons learned in the classification of errors, and present recommended guidelines for error data collection.

2.1 Description of JSS Project

JSS is a complex air defense system for North America. Seven regional control centers supported by 86 sensor sites provide the command, control, communications, and surveillance functions for this system. The system provides for the transfer of sensor data from the sites to the regional control centers, the lateral-tell of track and status information between centers, forward-tell of track and status information between centers, and the forward-tell of all information from the centers to a central operations center. The system is capable of operating in standard and degraded modes, and can provide backup capability for interfacing systems. Nearly 30 positional consoles and 10 remote access terminals support the operation of each regional control center.

The embedded software is configured in seven CPCIs and totals nearly 6,000 modules which are coded in Jovial (J3). This translates to nearly 330,000 DSLOC. There were nearly 2,000 software changes at the compilation unit level during development that were the result of changes to the requirements. Of the total deliverable compilation units, 82 percent were affected by these changes. The changes in the requirements included both clarifications and enhancements. Between the time at which the software was placed under configuration control and project week 192, approximately 6,000 actual errors had been detected.

2.2 Development Process for JSS Software

The development was performed in two major phases: design verification (DVP) and implementation (IP). At the peak of IP over 100 persons worked on software development. Approximately 40 percent of the software was "lifted" from previous air defense projects. Most of the lifted software was copied at the Computer Program Component (CPC) design level in the form of structure charts. Design at the intramodule level was copied in

the form of HIPOs. It should be noted that the lifted software could contain residual errors. Micro-phases completed within the IP were requirements analysis, design, coding, parameter and assembly test, integration, independent test, and system test. The project is now in the installation phase which includes on-site verification (OSV) testing for each of the regional control centers in the surveillance network. As of project week 192 three of the seven centers had successfully completed OSV testing and were operational.

In developing JSS, Hughes followed the software development phases generally accepted by the industry and the Government. Those phases are: requirements analysis, design, coding, parameter and assembly testing (also called unit testing), software integration, independent testing, system testing, and installation testing. One exception was the omission of parameter and assembly testing for those clusters of modules which were lifted from existing Hughes systems.

2.2.1 Requirements Analysis The JSS software requirement specifications were written by the lead systems engineering group, the Systems Division. Generally the Software Engineering Division (SED) is consulted or participates in the generation of these specifications. However, the first stage for which SED is officially responsible is analysis of the specification. This phase consists of assessing the feasibility of implementing the specifications in software, determining if there is existing software responsive to similar requirements, and generating independent test plans based on specification requirements.

2.2.2 Design Hughes employs a programmer team concept organized by CPC or in some cases by Computer Program Configuration Item (CPCI). Examples of CPCs are weapons, surveillance, data recording, and displays. On JSS the System Exercise Set (SES), a CPCI, was small enough to be developed by one team. The team leader is completely responsible for the detailed design, coding, and checkout of the software in the particular CPC. As a rule, modules undergo code reviews by the team leader, and upon successful completion of the review are usually placed under configuration control. Most of the JSS modules were placed under configuration control after completion of parameter and assembly testing.

Hughes-Fullerton employs an adaptation of Constantine and Yourdon's (YC, 1975) structured design methodology for decomposition of the software design to the module level. Intramodule design is controlled by SED training courses, individual project standards, and detailed design reviews.

Most JSS development teams utilized the cross-compiler and computer system simulation capabilities of both the Software Development System (PDP 11/70) and the Amdahl 470 during this

phase. Although the simulator has some I/O simulation limitations, its use was productive in detecting errors early in the development when target computer time was saturated.

2.2.3 Coding Hughes coding standards restrict programming control structure to the five basic structures: Sequence, If-Then-Else, Do While, Do Until, and Case. The standards also contain module and data naming conventions, as well as statement labeling conventions. Each module must have a single entry and single exit, and no self-modification of statements during execution is allowed. Like most recent air defense applications, JSS was coded in the Jovial high order language, and the direct code option was limited to special timing situations such as the on-line performance monitoring function (This function periodically checks the system status, and cannot compete with the application operation cycle).

2.2.4 Parameter and Assembly Testing Parameter and assembly tests provide for the testing of specific modules or groups of modules in preparation for integrating them into the system master version. These tests emphasize the internal processing of modules and are performed by the programmer who coded the modules. The main objective of parameter and assembly testing is to ensure that the modules under consideration are reasonably complete before further testing on a broader scale, and that each module or group of modules functions properly in isolation. Informal test procedures and reports are generated by the programmer and approved by the team leader.

2.2.5 Software Integration The software integration activity is an orderly sequence of putting modules together to perform software subsystem functions in accordance with an integration or build plan. This activity emphasizes interfaces between modules, and ensures that modules will function as designed in the latest system configuration. Some degree of testing must be performed in integration to provide confidence that a complete function operates as designed, but not necessarily that the entire system operates correctly. The activity is directed by a software integration coordinator, and the deliverable hardware set is used.

2.2.6 Independent Testing The independent tests validate that the performance specifications are implemented properly. The testing is performed by a test team that is organizationally independent of the development group that designed and coded the software. Test plans and detailed test procedures are written to validate each requirement (i.e., "shall" statements) of the CPCI functional Part I specifications. All external inputs are simulated, and the deliverable hardware configuration is employed. Tests are sensitive to intermediate processing results, and can detect design, coding, and interface problems.

Some statistics about the independent testing activity exemplify the size of this effort on the JSS Project. There were

nine software test engineers, including a team leader, assigned to the independent test team. A total of 143 test procedures with 14,277 test steps were generated and conducted for the seven CPCIs. The team expended 30,332 manhours over 32 calendar months in performing the independent test activity. The distribution of effort for detailed activities was: test plan generation (15%), test procedure generation (35%), and test conduct and analysis (50%).

2.2.7 System Testing System tests are formal acceptance demonstrations of hardware and software elements of the deliverable operational configuration, which are performed in plant. The software portion is demonstrated with the operational hardware complement by formal qualification verification (FQV) tests which are mutually agreed upon by the contractor and customer. On JSS forty-six FQV test procedures were run to exercise the seven CPCIs as well as an overall load test. The procedures were written against the system specification (Type A), and also written to the requirements "shall" level. A JSS FQV test procedure averaged 121 pages in length. The test procedures were performed by a team of fourteen test engineers from the Systems Division with the assistance of three test engineers from the Software Engineering Division. The tests were conducted over a two-month period, and witnessed and approved by the customer.

2.2.8 Installation Testing Installation testing consists of two phases - Installation and Checkout, and On-Site Verification (OSV), in that order. The installation and checkout activities pertain to hardware only, and include air cooling, power-on, and voltage checks on the delivered hardware configuration. The OSV tests are one level higher than the system tests in that they demonstrate that the system can complete a mission scenario. Both live and simulated external inputs are used. The OSV tests detect software errors predominantly, since the installation and checkout tests uncover most of the hardware faults. Further operational testing such as Qualification OT&E is the responsibility of the customer with the support of the developer.

On JSS there were twenty-two OSV test procedures conducted by a team of 10 test engineers including the team leader. Most of the OSV tests were performed at each of the seven ROCC sites, however special tests such as software reliability, weather, and peak load were performed at selected sites only. During live OSV tests eight different interceptor types were exercised. JSS OSV tests concentrated on site-to-site interfaces and system timing characteristics.

2.3 Input Data Requirements for Models

The exact input data requirements for the six models (Geometric Poisson, Imperfect Debugging, Non-Homogeneous Poisson, Generalized Poisson, IBM Poisson, Binomial) are listed in Table 2.3.1.

With only a few exceptions, the exact data input requirements could be met with the JSS data. A serious exception occurred with the Imperfect Debugging Model (Goel, 1978) since the exact times between successive software errors were not retrievable from the JSS database. Moreover, it is also not possible to make a perfect determination of whether or not an error is due to imperfect debugging (i.e. failure to completely remove an error) based on the data collected on a PTR. In fact, many maintenance PTR's are new errors created in the process of removing a previous error rather than the recurrence of the previous error due to imperfect debugging. Thus, the indicator variables in Table 2.3.1 for the Imperfect Debugging Model are also irretrievable. These considerations will be discussed in Section 3, along with rationale for employing a different model in place of the Imperfect Debugging model.

Another exception occurred with the Geometric Poisson Model, although in this case the exception was minor and easily corrected. The requirement that errors be compiled in equal, non-overlapping time intervals was not always convenient. However, using all the assumptions and principles in Moranda (1975) it was possible to modify the likelihood function in Moranda (1975) to account for time intervals of varying length and thus to fit the Geometric Poisson Model under these conditions. See Section 3 for further discussion of the Geometric Poisson Model.

The last exception is relatively minor in most cases. One of the assumptions of the Imperfect Debugging Model (and tacitly assumed in all the other models) is that when an error is detected, it is immediately removed and the removal time or "correction" time is negligible. If this correction time is not negligible, then it must not be counted as part of the time interval during debugging. In the JSS database, the correction time for each error is not available and cannot be recovered, and thus we have assumed throughout this report that it is, indeed, negligible.

In view of the presentation given in Brooks & Motley (1980) for the IBM Poisson Model, the list of data input requirements in Table 2.3.1 seems simplistic, and must be explained. The IBM Poisson Model is a rather in-depth generalization of the Jelinski-Moranda model and it allows the user to consider several groups of software modules at once. To do this, it takes into account the number of errors detected in each module in each group, the fraction of these errors removed, the fraction of the system which is under test, and various other quantities. In view of the time and budget constraints for this effort, and the lack of much of the supporting data necessary to fit the IBM model in its complete generality, we chose to fit the model at the

module (actually, compilation unit) level so that the computations and data requirements would be simpler. Under these conditions, the input data requirements reduce to those listed in Table 2.3.1.

In surveying the references listed in Table 2.3.1, it was surprising that no author was explicit in specifying the manner in which time was to be measured, or whether the models should be applied during particular software test phases (e.g., integration test, system test, independent test, etc.). Due to varying manpower and the gradual build-up of software on a typical software project, it is doubtful that calendar time is an adequate time scale. Brooks & Motley (1980) accounted for software build-up in their IBM Poisson Model, but no other author recognized these potential problems with the time scale. The JSS database was carefully monitored to ensure that there were no anomolies in recording the resolve dates for the PTR's, and the supplemental database (See Vol. II) contains information describing the rate of software build-up. However, there was no way to control and monitor manpower loading, and calendar time was the only time measure available on JSS. While execution time is perhaps a better time measure, schedule and budget constraints on JSS would not allow for its procurement.

In terms of the question of test phase in relation to fitting the models, there was prior evidence that this could be an important factor. In particular, Goel (1980, p. 43) found it necessary to eliminate data from the first nine out of ten weeks of the validation phase of formal testing in his database in order to obtain the decreasing trend in his data necessary to achieve a good fit in the Nonhomogeneous Poisson Model. This would tend to support the conjecture that the models may be test phase sensitive. For this reason, the additional data item "test phase" should be tacitly assumed as an additional data input requirement for each model. Of course, test phase was routinely collected in relation to each PTR in the JSS database.

Table 2.3.1

Input Data Requirements for Software Reliability Models

Model	References	Input Data Requirements
Geometric Poisson	Moranda, 1975	o The numbers of software errors in successive, non-overlapping equal calendar time periods
Nonhomogeneous Poisson	Goel & Okumoto, 1980	o The numbers of software errors in successive, non-overlapping calendar time periods, and the lengths of time periods, or the calendar times between successive software errors.
Imperfect Debugging	Goel, 1978	o Calendar times t_1, t_2, ..., t_n between successive software errors. o Indicator variables y_1, y_2, ..., y_n with $y_i = 1$ if the i^{th} error is caused by imperfect debugging, $y_i = 0$ otherwise. o The calendar time to remove each error if this time is not negligible.
Generalized Poisson	Schafer, et. al. 1979	o The numbers of software errors in successive non-overlapping calendar time periods, and the lengths of the time periods. o The numbers of software errors removed in successive non-overlapping calendar time periods.

Binomial	Schafer,et.al. 1979	o The numbers of software errors in successive, non-overlapping calendar time periods, and the lengths of the time periods.
IBM Poisson	Brooks & Motley, 1980	o The numbers of software errors in successive non-overlapping test time intervals, and the length of each time interval,

2.4 Guidelines for Software Error Data Collection

A comprehensive survey study of the experience in the collection of data related to the software development process (Thibodeau, 1979) reports that the same mistakes in the data collection process have been repeated over and over again. The report concluded that if we intend to develop quantitative relationships between software errors and their causes then we need to develop 1) automated data collection techniques, 2) consistent definitions, and 3) a more manageable error classification system. This section contains guidelines for collecting error data for use with quantitative software reliability models and metrics. These guidelines are based on Hughes-Fullerton's experience in collecting software error data from ongoing software development projects such as JSS that use a semiautomatic data collection system and a manageable and standard error classification scheme.

It should be understood that the guidelines presented here are for the collection of error-related data necessary for the direct input into quantitative software reliability models and into their attendant estimator algorithms. The data must be collected during the software development phases in order for the models or metrics to provide either immediate assessment or predictive values. As it will be seen, data in addition to that required for direct input into the models and metrics is suggested to be collected to support data validation and to provide reference material for research.

2.4.1 Approach

The overall approach to any error data collection activity is to collect as much related data as feasible (without perturbing important project milestones) from the selected software development project. This approach allows for redirection during the project to accommodate new models and metrics of interest. Furthermore the collection of some redundant data aids in the validation process.

A significant approach, especially with respect to the encouragement of cooperation from the software projects, is to develop a data collection procedure that has a minimum requirement for participation by the project. For example, the use of straightforward error categories and menu-formatted input requests serve to minimize the extra time required by project personnel.

2.4.2 Indoctrination

No one likes to be associated with committing an error. This is especially true in software where the manifestations of the error may be catastrophic, expensive, or curtail the progress

of team members. Consequently, the psychological aspects of being responsible for an error should be dealt with early-on in a project where error data collection will be performed. It is worthwhile to view an error as a phenomenon of programming which requires study. While it is necessary to be sensitive to programmer's reactions when threatened by exposure of their errors, it is probably healthier to get the errors and the errant out in the open rather than to cover up the human origin of errors. All project personnel should be informed of the purpose of the data collection, and fully trained in the use of the associated procedures and classifications.

Programmers must be indoctrinated as to the importance of collecting complete and accurate data for an upcoming software engineering study. Every effort must be taken to provide error classification codes and definitions at the programmer's work stations. If the codes are not readily available, programmers will tend to use the same set of error codes for all situations. Programmers and test engineers must also be reminded that they should report all errors and not fall to the temptation of fixing a distinguishable error as a undocumented add-on to another error which is in work.

2.4.3 Classification

For the purpose of supporting software reliability models, most agree that a standard error classification is preferred [Bowen, 1980]. It is mandatory that the definitions of the error data collected be consistent with the definitions of the input parameters of the software reliability models employed. For example, one of Goel's models (Goel, 1978) includes the imperfect debugging phenomenon. This error class must be clearly defined as the incomplete or incorrect correction of a previously documented error. If the original activity was a requirements change and not a correction then an associated erroneous fix would not qualify as an imperfect debugging class error.

Existing problem reporting forms and configuration control systems allow for entries that are not just errors. Other entry classes include configuration control impounds, adaptive changes, updates from master programs, and new requirements. Other obvious extraneous entries are duplicate problem report and problem rejection. Accordingly each entry must be classified by at least a cause category to allow selection of qualified entries from the database.

Hughes-Fullerton has found that a minimal set of two software error classifications (Phase/Cause and Severity) as well as the erroneous subprogram/module are required to support the evaluation of software reliability quantitative models. Phase/Cause tells in which software development phase the error was

introduced and what the programmer or analyst did wrong. Severity tells whether the manifestation of the error degrades the system mission performance. The identification of the subprogram/module allows for reliability assessment to the functional level.

On the JSS project a separate classification scheme was employed for source phase and cause. The following error causal classification scheme, which was tailored from an RADC scheme [Thayer, 1976], was used. Of the sixteen categories, four (I00, J05, J30, and J60) did not quality as error-related.

- A00 -- Computational
- B00 -- Logic
- C00 -- Data Definition
- D00 -- Data Handling
- E00 -- Design
- F00 -- Interface
- G00 -- Compool (Communications pool)
- I00 -- Problem Report Rejection
- J00 -- Other
- J05 -- Test-Only Code
- J10 -- Timing Optimization
- J20 -- Sizing Optimization
- J30 -- Integration of New Software
- J50 -- Unnecessary Code
- J60 -- New Requirements/Enhancements
- J90 -- Standard Violation

Some problems were encountered with consistent interpretation of the JSS causal categories. For example, there was not a clear distinction between Compool (G00) and Data Definition (C00). In most instances G00 was used for any change to the CPCI global compools, and C00 was used for specific error-related changes for preset values or table structures for local data. Another confusing category was Integration of New Software (J30). This category was intended to identify the impound of new software modules, however some programmers used J30 when adding to an existing module (whether for correcting an error or for implementing a new requirement) or for any error encountered when integrating software to software. Fortunately most of the resulting inaccurate classifications were obvious when related PTR data was compared, and the inaccuracies were corrected. For example, if a programmer or librarian assigned the error cause J30, and the new version field for the affected module is not "1.1" then an inconsistency exists. This is because impounded modules should have a version number of 1.1 (unless special arrangements are made to retain previous version numbers for lifted modules).

There are several methods of recording an imperfect debugging error. An Imperfect Debugging major causal category can be added to the other major causal category, or an Imperfect Debugging category can be added to the source phase classification. On JSS, imperfect debugging was identified by the source phase category of Maintenance (MN). If separate error cause and source phase classificatons are employed (as was the case on JSS), then it is recommended that the Imperfect Debugging category be added to the source phase classification, because including it as a causal subcategory would preclude the assignment of the more descriptive cause, such as interface error. However if a combined phase/cause classification scheme is employed as suggested later in the report, the needs of software reliability models are adequately supported.

Maintenance errors, or regression errors as they are sometimes called, accounted for only four percent of the total errors detected through week 192 of the JSS project. Just considering the Installation phase, the percentage was twenty percent. Two reasons could account for this difference. One is that a different configuration control system was used during the installation phase than in the previous phase. The system employed during installation is more supportive of recording multiple attempts to resolve a PTR than the automated system employed in plant. The other reason is that the acceptance testing schedule places extra pressure on programmers to resolve errors quickly, and consequently maintenance errors increase. The maintenance errors reported on JSS were predominantely of the incorrect solution or bad patch variety and few or none were of the incompatible or ripple effect variety.

In consideration of the direction of the Joint Logistics Commanders [Hartwick 1979] and the persistent complaint from the programmers assigned to classify errors that the existing schemes have too many categories, we recommend the following combined source phase/causal error classification scheme for the support of software reliability modeling.

- REQUIREMENTS
  - R1 Incorrect Specification
  - R2 Conflicting Specification
  - R3 Incomplete Specification
- DESIGN
  - D1 Requirements Compliance
  - D2 Choice of Algorithms
  - D3 Sequence of Operations
  - D4 Data Definition
  - D5 Interface
- CODING
  - C1 Requirement or Design Compliance
  - C2 Computation Implementation
  - C3 Sequence of Operations
  - C4 Data Definition
  - C5 Data Handling
  - C6 Omitted Logic
  - C7 Interface
- MAINTENANCE
  - M1 Incorrect Fix
  - M2 Incompatible Fix
  - M3 Incomplete Fix
- OTHER

- (Nonreliability-related errors)

To assist error classifiers, we propose that the complete classification scheme, incuding codes and brief definitions, be printed on the back of the hard copy PTR form, and also be callable as a Help file during interactive mode error classification.

2.4.4 When To Start

Software engineers generally agree that error data collection should start as early as possible, in other words during the requirements analysis phase. Unfortunately, many software developers or programmers resist error recording until as late as the integration phase. Most projects start recording error data as early as the coding phase during software inspections or code reviews. At Hughes-Fullerton, only the causal classification of the error is recorded during code reviews. This data is useful for providing immediate feedback for evaluating the software development process, however by itself it is not supportive to the typical reliability model. This is because a code review is a scheduled one-time evaluation and does not have progressive time-related characteristics that are required by most models. Data collected during the checkout phase can be biased by the influence of the individual programmer's approach to debugging. Most programmers design module or unit tests that show the absence of errors rather than have a high probability of detecting errors. Other variables include whether or not a programmer desk checks his or her code prior to using static and dynamic test analyzers.

A common factor that influences when to start collecting error data is the existence of a configuration control system. Most automated configuration control or program development library schemes control the access to modules that the programming staff has submitted for integration into the system under development. Accordingly each time a change is made to a module under configuration control, records of the change are automatically generated. In order to take advantage of this automatic data collection, most error data collection starts after software is placed under configuration control.

Since most reliability models and metrics are used in a predictive context it follows that more accurate results will be obtained by using input data that more closely represents operational data. The operational scenario during the formal acceptance test phases is thought to be more representative of actual system operation than the earlier development phases.

2.4.5 Procedure

Hughes-Fullerton has converted from semiautomatic to completely automatic configuration control systems for software development projects. Most projects that started in 1981 are

using the automated configuration control system which is an integral part of the Programmers Workbench. This system contains a separate entry for each Program Trouble Report (PTR). The system includes special commands for entering and changing PTR data as the problem proceeds through each step such as the Software Change Review Board action, assignment to group for resolution, submittal of resolution to the Librarian, and verification of the resolution after incorporation in the next system version. Each PTR-related command has an associated privilege that permits only authorized entries or changes to the data. Commands are also available to generate summary reports.

Some new projects, due to their sensitivity or security classification cannot be accommodated by the automated version of the configuration control system. Other projects cannot use the automated system because of the inaccessibility of the system either due to physical location or cost. Since we have had recent experience in collecting the same error data from both the semiautomated and fully automated systems, some comparisons are noteworthy. We have encountered more problems in the area of programmer/analyst-supplied information in the newer automated system than in the earlier systems.

Naturally, some difficulties are to be expected due to the implementation of a new system, however, another influence is involved. This influence is the propensity of programmer/analysts to use short cuts in the automated system. A typical example of this situation is the closure of a PTR as a "no change" when in fact there was a change. In the current automated system no-change entries are not required to have the associated classifications and data entries. The author of a pseudo no-change justifies such a resolution by noting in the comments field that the PTR was resolved under another PTR. Even in such cases where the reference is given to the action PTR, the actual resolution data is overridden inherently, because the erroneous software is identified only to the compilation unit level. Such shortcomings in the automated system point to the need for more automated and human-performed validations.

The JSS data collection procedure utilizes the configuration control system which is part of an automated interactive software development system. The basic data necessary for input to the software reliability models (date detected, Cause, Severity, Source Phase, Module Name, and date resolved) are automatically entered into the configuration control system by program trouble report number, prompted by a menu format. The basic data which is recorded by PTR is shown in the accompanying PTR report (Figure 2.4.1) which may be generated for each PTR.

A special error qualifier computer program was developed that screens the PTR database for those entries that have causal categories that qualify as reliability-related. These qualified entries are then consolidated and reformatted to include only

Figure 2.4.1 Format of Individual Program Trouble Reports.

```
TITLE: illegal v{r used in split evnt                         PTR NO.: 09991

ORIGINATOR : pwong       DATE OF ORIGINATION : 140          PTR STATUS : c

RESOLVED BY: jsslib      DATE OF RESOLUTION  : 141
VERIFIED BY: jheyl       DATE OF VERIFICATION: 142          PTR TYPE   : p

                         RESIDENT COMPUTER:c   OLD SYSTEM VERSION: dr3401
COMMENTS :                                     NEW SYSTEM VERSION: dr3501
=============================================================================
DESCRIPTIVE TEXT:
the value of the variable is wiped out because another variable is overlayed
to the same location.


=============================================================================

DOCUMENT AFFECTED:       PHASE DETECTED : it      PERFORMANCE EFFECT: mi

ASSIGNED GROUP   : dr    PTR COORDINATOR: jheyl

MODULE NAME                 C T PH CLS GR PROGMR OLDVRS NEWVRS COMMENTS
drs/brd.j                   g g co d00 rb pwong  1.9    1.10
drs/bzd.j                   g g co d00 rb pwong  1.10   1.11
drs/grd.j                   g g co d00 rg pwong  1.9    1.10
```

Figure 2.4.2. Sample of Error Data File Format.

PTRNo	Short Title	SysVer	Gr	CU	Det	Res	Ver	PC	PD	Cls	Ef	ROCC/ Co-ord
09350	fdr-01 capacity tr/frm field	dr3504	rd	dad	134	144	145	co	st	b00	ma	jheyl
09418	m4 request/reply processing	dr3301	rb	bgd	135	136	136	co	it	b00	mi	jheyl
09420	event time of m4 req/rep	dr3301	rb	bgd	135	136	136	co	it	b00	mi	jheyl
09469	jq/jr - pace output unit	dr3302	rp	pdd	135	136	137	co	it	c00	mi	jheyl
09488	regstr wiped out/closed stmn	dr3303	rg	gtd	135	136	138	co	it	b00	ma	jheyl
09491	rply corr e-o-reply record	dr3302	rg	gvd	135	136	137	co	it	c00	mi	jheyl
09492	replay corr sxx para table	dr3302	rg	gvd	135	136	137	co	it	c00	mi	jheyl
09524	lix - field length	dr3302	rg	gwd	135	136	137	co	it	b00	mi	jheyl
09523	jd for variable used twice	dr3302	rg	gfd	135	136	137	co	it	c00	ma	jheyl
09529	jd - output fields omitted	dr3302	rg	gfd	135	136	137	co	it	e00	ma	jheyl
09530	jd overlay locat'n clac inco	dr3302	rb	bfd	135	136	137	co	it	a00	mi	jheyl
09538	mode 4 corr indicator	dr3302	rg	gld	135	136	136	co	it	f00	mi	jheyl
09542	select sense(2) processing	dr3302	rs	sad	135	138	138	co	it	b00	mi	jheyl
09419	jg summary report	dr3401	rb	bid	135	139	139	co	it	b00	mi	jheyl
09523	lix - reorganization	dr3401	rb	bwd	135	139	140	co	it	b00	mi	jheyl
09525	lix - anded keys	dr3401	rb	bwd	135	139	140	co	it	b00	ma	jheyl
09526	lix - display code conversio	dr3401	rg	gwd	135	139	140	co	it	b00	mi	jheyl
09527	sa/sb - no trn/srn qual.	dr3401	rb	bwd	135	139	140	co	it	b00	mi	jheyl
09547	mode 2/mode 3 code	dr3302	rb	bld	136	136	136	co	it	b00	mi	jheyl
09576	corr int time/frame	dr3303	rb	bld	136	137	137	co	it	b00	mi	jheyl
09578	correlation mode	dr3303	rg	gld	136	137	137	co	it	b00	mi	jheyl
09609	non-matching sif code	dr3303	rb	bld	136	137	137	co	it	b00	mi	jheyl
09610	pace - no max rng on height	dr3303	rp	pgd	136	137	138	co	it	b00	mi	jheyl
09637	lat tell/tty corrections	dr3401	rg	gvd	136	137	140	co	it	f00	mi	jheyl
09560	restart - zero trap	dr3401	rc	cad	136	139	140	co	it	d00	cr	jheyl
09629	idra-12a jj fld 5 opt err	dr3504	rd	dad	136	144	144	co	sd	b00	mi	jheyl
09641	pcd zero trap	dr3303	rp	pcd	137	137	138	co	it	c00	cr	jheyl
09645	jd-init module call omitted	dr3303	rb	bfd	137	137	138	co	it	b00	ma	jheyl
09646	jd-wrong recording time save	dr3303	rb	bfd	137	137	138	co	it	d00	mi	jheyl
09647	jd-aps tbl itms used incorr'	dr3303	rb	bfd	137	137	138	co	it	f00	ma	jheyl
09648	jd-disk block no not saved	dr3303	rb	bfd	137	137	138	co	it	b00	ma	jheyl
09649	jd-for loops setup incorr'ly	dr3303	rb	bfd	137	137	138	co	it	b00	mi	jheyl

those items of interest to the software reliability models and metrics. The resulting qualified data is then sorted by subprogram and date detected, and then placed in separate files for each subprogram. Each file, in turn, can be input almost directly into the computerized version of the reliability model or metric. The hard copy format (see Figure 2.4.2) of the files also can serve as a historical document for additional research.

2.4.6 Data Validation

Error data classifications must be continually validated for accuracy and consistency. As much of the monitoring as possible should be automated, however there will always be the need for human intervention to monitor those classification entries that are more subjective. Manual monitoring should be done for error-prone areas on a regular basis. Other data should be checked as required by sampling.

We have found that during the testing phases -- starting with integration -- that data collection can easily be preempted. It is expected that the pressures of formal testing will degrade the quality of the associated data collection. Therefore it is recommended that a quality engineer who is independent of the development organization be assigned to a project during formal testing for the purpose of obtaining accurate software error data during a phase when both time and tempers can be short.

When anomalies are found in the data collection procedures or classifications, every effort must be taken to have the anomalies corrected. It is essential that these corrections be made quickly so that no sloppy habits or trends develop. Isolated cases involving errors of minor severity or requiring the time of a software development team that is under pressure to meet schedule, usually can be discarded without biasing the model or metric results. If manpower loads permit, a senior project person should be assigned to troubleshoot and coordinate all data collection discrepancies found by the monitoring and auditing activities. In most cases such a troubleshooter can resolve anomalies without interfering with the progress of the project's development.

2.5 Perspectives on Data Collection Costs

One hinderanc[illegible]l software error data collection, until recently, has been the lack of specification by customers of specific quality factors of interest (e.g., reliability). Now, with the advent of standards such as MIL-STD-SDS and MIL-STD-SQAM software quality requirements and supporting metrics are being defined. The FAA Advanced Automation System RFP [FAA, 1983] includes comprehensive requirements for software error data collection. In addition to the typical MIL-S-52779A software problem reporting, analysis, and corrective action system plan; the RFP specifies a computer program reliability data collection

and reporting plan: "This plan will determine how computer program reliability parameters will be calculated, determine what information is necessary, and establish the methods and means of data acquisition." The definition of data collection requirements early in the acquisition phase provides a better understanding of the purpose of the task and in turn an accurate allocation of funds to perform the task.

Our experience in performing the data collection task for this study can be used to estimate the cost of data collection. In terms of person-hours the data collection and monitoring task represented 0.6 percent of the overall software development effort. Based on the actual person hours spent on the data collection task of the RMD study the cost per program trouble report was 0.398 person-hours and the cost per software module was 0.403 person-hours. The data collection effort includes the development of two computer programs (an error qualifier program and a report generator program), weekly quality monitoring of error classifications, and monthly editing and transmittal of the output file. Costs associated with the recording of errors (PTRs) using the configuration control system were not included in the data collection effort, but were included in the software development effort.

2.6 Distribution Analysis of the PTR Database

Several distribution analyses of items of interest within the JSS database were performed during the study and reported on a regular basis. These analyses included errors per module by CPCI, error performance effect for the entire project, phase detected for the entire project, error cause for the entire project, and monthly error rate for the entire project.

The analysis results of errors per module was very interesting because of the variance by CPCI. The percentage of lifted design is one factor that influenced this variance. The results listed in the following table do not show a linear correspondence between lifted design and errors, however. Notice that the application set (APS) has the highest error density (2.18), but lies in the middle of the lifted design range with a 40 percent value. These results tend to indicate that the more balanced the lifted design and new design, the more error prone is the resulting software.

CPCI	Errors	Modules	Lifted Design (%)	Errors/ Module
APS	3,462	1,642	40	2.11
OSS	910	682	47	1.33
SES	287	465	3	0.62
DRS	712	1,069	6	0.67
DIS	430	1,175	89	0.37
SUS	215	892	82	0.24

The following table summarizes the effectiveness of the various testing phases on JSS. The percent of total errors detected values for both integration and installation testing are high, and suggest the need for improvement in preceeding test phases. Although there are some errors in the database that were detected during Parameter and Assembly testing (4.8%), they are not included because most unit testing was performed prior to placing modules under configuration control.

Test Phase	Errors Detected (% of Total Testing)
Integration	36.9
Independent Testing	23.5
System Testing (FQV)	18.7
Installation Testing (OSV)	16.1
Operation & Support (QOT&E)	0.0
Total	95.2

Of the entries in the JSS PTR database with error causal classifications (5,232 of the total 6,016), the distribution by cause (see following table) reveals that Logic errors account for forty-four percent. This finding is in agreement with similar analyses such as Glass, 1981.

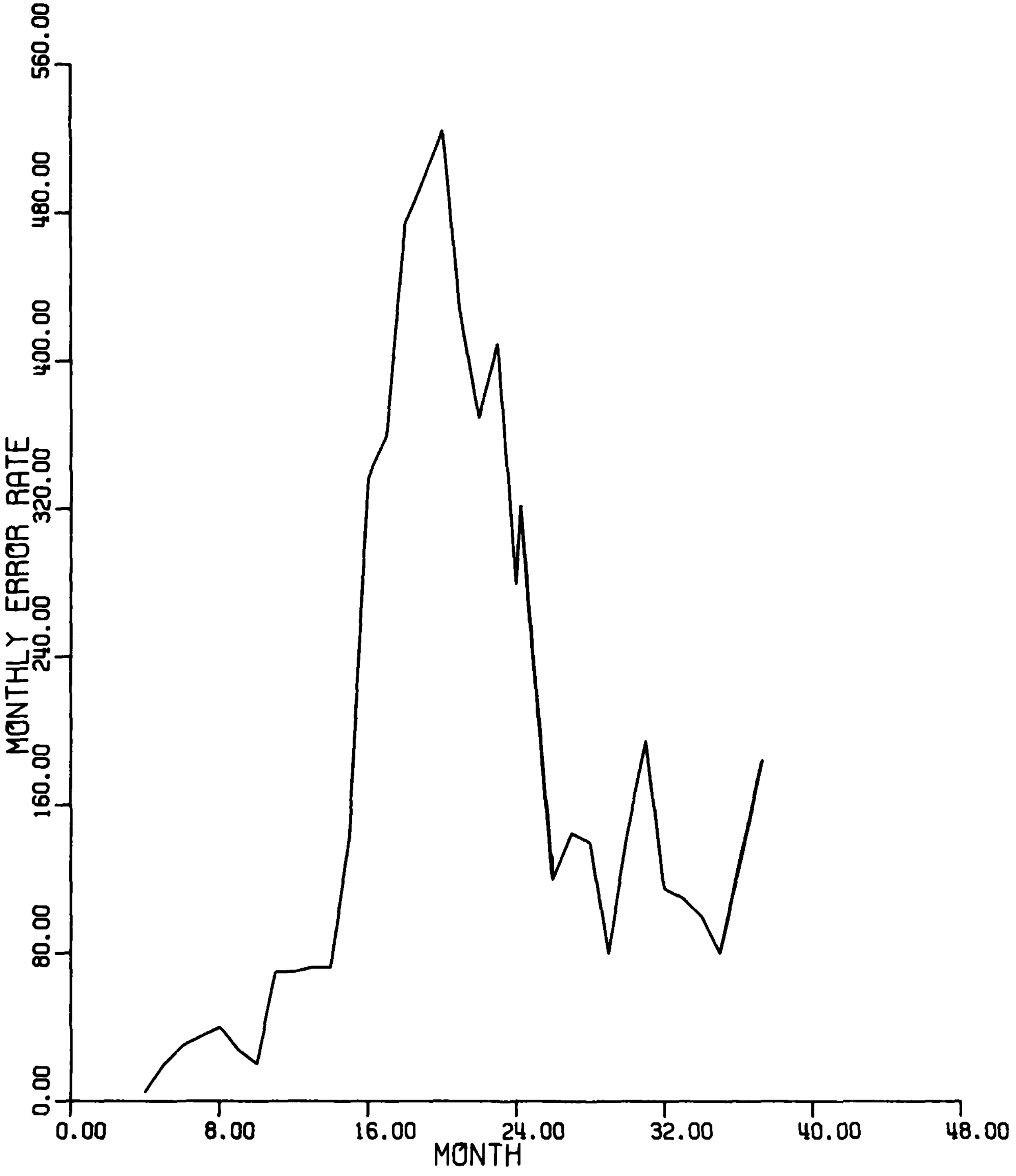
Casual Category	APS	DIS	DRS	OSS	SES	SUS	Total
Logic	41.7	54.1	52.1	41.6	25.4	57.2	43.7
Data handling	17.6	4.5	14.2	12.6	33.8	10.2	15.9
Interface	10.3	14.3	17.0	17.9	12.5	8.4	12.8
Design	15.4	8.0	4.1	9.1	9.2	10.2	11.8
Data Definition	10.7	13.0	8.4	15.0	8.8	10.2	11.2
Computation	2.7	1.6	3.1	2.0	8.1	3.7	2.9
Standards	1.1	4.0	0.6	1.6	1.8	0.0	1.3
Other	0.5	0.5	0.3	0.2	0.4	0.0	0.5
Total	100.0	100.0	99.8	100.0	100.0	99.9	100.0

The performance effect distribution is of interest -- not because of any unusual or unexpected results -- but because of the significance of qualifying errors detected during development for use with software reliability models. It has been suggested that only the categories of Critical and Major are applicable to predicting operational reliability. As shown in the following table only 44 percent of the database entries qualify as Critical or Major.

Performance Effect	Percent of Total
Critical	6.4
Major	37.3
Minor	56.3
Total	100.0

The following Figure (2.6.1) summarizes the error detection rate on a monthly basis for the JSS software development from project week 50 through 192. Errors recorded during the first year of the project were not included. Even considering the fact that the data represents only errors recorded after software was placed under configuration control, the resulting

Figure 2.6.1. Monthly Error Detection Rate



skewness to the right indicates that errors were not detected as early in the development cycle as possible and as would be preferred. The spike at September 1981 (month 20) represents an overlap of the peak of integration testing and the early stage of independent testing , and the spikes at September 1982 (month 31) and March 1983 (month 36) are in the installation phase. It is noteworthy that these spikes illustrate a nondecreasing error rate which is contrary to the assumptions of most software reliability models.

2.7 Description of JSS Software Configuration

As mentioned earlier, the JSS software is decomposed into seven CPCIs. These CPCIs are further decomposed into CPCs or functional groups which are, in turn, decomposed into compilation units which are, in turn, decomposed into modules. For the purposes of this study, the System Control Set (SCS) was combined with the Operating System Set (OSS), because of the small size of the SCS. A summary of the hierarchy and size of the JSS software configuration is presented in Table 2.7.1. The table includes only entries that had qualified errors reported against them. In other words, the table does not contain all of the compilation units in the JSS software, and the total number of modules does not reach the totals presented earlier. The purpose of the table is to provide a convenient cross reference between compilation units and groups within each CPCI, and to define the size of each compilation unit in terms of number of modules. Note that compilation unit designators are not unique between CPCIs. (For example, compilation unit kaz in the Application set is not the same as compilation unit kaz in the Operating System set.) Based on a representative sample of 100 JSS modules the mean module size is 55 executable source statements and the median module size is 28.5 (This finding is of interest as it demonstrates how a few extremely long modules can distort the mean value, commonly prescribed in MIL-STDs, when used to monitor the module size tendency on a project).

Table 2.7.1. JSS Software Hierarchy

Set (CPCI)/Group (CPC)	Group (Gr)	Compilation Unit (CU)	Nr. of Modules
Application Set (APS)			
Active Correlation	aa		
		aad	8
		abz	9
		acz	55
		add	10
		agd	2
		aiz	3
		alz	1
		aqz	1
		arz	1
		asz	1
		atz	1
		auz	1
Action Entry Input	ab		
		baz	15
		bhz	20
Console Broadcast	ac		
		cad	3
		caz	1
		cbz	1
		cdz	4
Displays	ad		
		daz	88
		dbz	1
		dcz	1
		ddz	10
		dtz	2
Realtime Control	ae		
		ecz	19
		edz	12
		efa	1
		efz	1
		egz	1
		eiz	2
		ejz	1
		emd	1
		emz	1
		enz	1
		eoz	1
		epz	5
		erb	1

Table 2.7.1. JSS Software Hierarchy (Continued)

Set (CPCI)/Group (CPC)	Group (Gr)	Compilation Unit (CU)	Nr. of Modules
		esz	1
		etz	1
		evz	1
		exz	1
		eyz	1
		ezz	1
Flight Plans	af		
		faz	4
		fbz	1
		fcz	2
		fdz	2
		fez	1
		ffz	1
Mode 4	ag		
		gaz	1
		gbz	1
		gez	1
		gfz	1
		gmz	1
		gwz	1
Height	ah		
		haz	1
		hbz	1
		hcz	1
		hnz	1
		htz	42
		hvz	1
TDDL	aj		
		jaz	18
E-3A Initialization	ak		
		kaz	20
		kbz	1
		kcz	1
		kdz	6
		kez	1
		kfz	4
		khz	1
		kjz	1
		kkz	1
		klz	5
		krz	1

Table 2.7.1. JSS Software Hierarchy (Continued)

Set (CPCI)/Group (CPC)	Group (Gr)	Compilation Unit (CU)	Nr. of Modules
Telling Output	al		
		laz	1
		lbz	1
		lcz	1
		lfz	9
		llz	1
		lqz	1
		ltz	21
		lxz	5
Manual Inputs	am		
		maz	1
		mbz	3
		mcz	1
		mez	7
		mfz	9
		mgz	3
		miz	6
		mjz	1
		mkz	5
		mlz	3
		mnz	1
		moz	1
		mpz	1
		mqz	2
		mrz	5
		msz	1
		mtz	11
		mwz	7
		mxz	1
Auto Inputs	an		
		naz	13
		ncz	16
		nfz	13
		niz	1
		noz	1
		nqz	1
		nrz	5
		nuz	5
		nzz	1

Table 2.7.1. JSS Software Hierarchy (Continued)

Set (CPCI)/Group (CPC)	Group (Gr)	Compilation Unit (CU)	Nr. of Modules
Replay	ao		
		oad	1
		oaz	1
		obz	1
		ocz	1
		odz	4
		oiz	5
		olz	1
		orz	12
		otz	1
		oyz	1
		ozz	1
Passive Correlation	ap		
		pcz	1
		pez	1
RTQC	aq		
		qaz	25
		qbz	24
		qoz	9
		qtz	1
Recording	ar		
		raz	1
		rbz	1
		rcz	1
		rdz	4
		rez	17
		rfz	8
		rqz	1
		rjz	1
		rmz	1
		rnz	1
		roz	9
		rpz	3
		rqz	1
		rtz	5
		ruz	1
		rwz	1
		rzz	1

Table 2.7.1. JSS Software Hierarchy (Continued)

Set (CPCI)/Group (CPC)	Group (Gr)	Compilation Unit (CU)	Nr. of Modules
Simulation	as		
		sad	35
		saz	4
		sbd	1
		sbz	11
		scd	1
		scz	1
		sdz	1
		sez	1
		skz	1
		slz	2
		smz	33
		srz	1
		ssz	1
		stz	1
		suz	3
Tracking	at	afd	1
		tad	24
		taz	1
		tbz	1
		tcz	1
		tdz	1
		tgz	1
		tsz	1
		tuz	34
		tvz	2
		twz	3
		tyz	21
Interceptor Control	au		
		uaz	1
		ubz	1
		ucz	1
		udz	1
		ufz	3
		ugz	3
		uhz	1
		uiz	1
		uoz	1
		upz	1
		uqz	1
		urz	1
		usz	1
		uuz	1
		uvz	1
		uwz	1
		uxz	1

Table 2.7.1. JSS Software Hierarchy (Continued)

Set (CPCI)/Group (CPC)	Group (Gr)	Compilation Unit (CU)	Nr. of Modules
Interceptor Control	aw		
		waz	1
		wbz	1
		wcz	1
		wdz	1
		wez	1
		wfz	1
		wgz	1
		whz	1
		wjz	1
		wkz	1
		wlz	1
		wmz	1
		wnz	1
		woz	1
		wpz	1
		wqz	1
		wrz	1
		wsz	1
		wuz	1
		wwz	1
		wxz	1
		wyz	1
		wzz	1
Telling Input	ax		
		xbz	1
		xcd	1
		xdc	1
		xdz	5
		xlz	16
		xtz	2
Action Entries	ay		
		yaz	1
		ybz	2
		ycz	1
		ydz	1
		ygz	1
		yhz	1
		yjz	1
		ykz	1
		ynz	1
		ypz	1
		yqz	1
		yvz	1
		ywz	1
		yzz	1

Table 2.7.1. JSS Software Hierarchy (Continued)

Set (CPCI)/Group (CPC)	Group (Gr)	Compilation Unit (CU)	Nr. of Modules
Action Entries	az		
		zaz	17
		zbz	4
		zcz	40
		zdz	49
		zez	21
		zjz	1
		zkz	25
		zlz	33
		zmz	1
		znz	1
		zoz	1
		zqz	1
		zrz	1
		zsz	1
		zuz	5
		zvz	1
		zwz	1
Site Adaptation		aka	N/A
		cea	N/A
		cwa	N/A
		nea	N/A
		nwa	N/A
		sea	N/A
		swa	N/A
Compool		apc	N/A
	Total		1,203

Table 2.7.1. JSS Software Hierarchy (Continued)

Set (CPCI)/Group (CPC)	Group (Gr)	Compilation Unit (CU)	Nr. of Modules
Diagnostic Set (DIS)			
Disk Test	da	dsk	31
Central Computer Interface Unit Test	db	ciu	5
Interference Test	dc	ift	80
Display Console Test	dd	hmd	22
Intercomputer Data Duplexer Test	de	icd	18
Magnetic Tape Test	df	mtu	3
Card Reader Test	dg	cdr	1
Controller Computer Support	dh	dix	43
Diagnostic Executive	di	cax	4
		cex	1
		cix	1
		cmx	6
		cpi	6
		cps	37
		cqx	1
		max	32
		sex	89
Memory Test	dk	cma	7
		cmb	1
		mem	19
Central Computer Manual Operations Test	dl	cpm	1

Table 2.7.1. JSS Software Hierarchy (Continued)

Set (CPCI)/Group (CPC)	Group (Gr)	Compilation Unit (CU)	Nr. of Modules
Controller Computer Processor Test	dm	cpa	24
		dpa	3
		dpb	17
Remote Access Terminal Test	do	rat	67
System Control Console Terminal Test	dp	sct	23
RMM Function	dq	rmb	1
		rmm	14
Line Printer Test	dr	hcp	18
		lpr	1
CMUX Test	ds	mux	26
Central Computer Buffered I/O Test	dt	bio	13
		unl	1
Central Computer Diagnostic Support	du	jax	15
		jbx	1
		jpx	1
		kdx	8
		rix	3
		spx	13
		srx	4
		tbt	4
Loaders	dv	ddl	48
		fbt	1
		fdl	25
		lac	29
		ldr	13
String Interface	dw	dis	23
Central Computer Dual Processor Test	dx	dul	25
Compool		dmc	N/A
		Total	829

Table 2.7.1. JSS Software Hierarchy (Continued)

Set (CPCI)/Group (CPC)	Group (Gr)	Compilation Unit (CU)	Nr. of Modules
Data Reduction Set (DRS)			
Build Intermediate File	rb	bed	19
		bfd	21
		bgd	29
		bid	16
		bkd	14
		bld	20
		bpd	17
		bqd	22
		brd	57
		bud	33
		bwd	33
		bxd	1
		bzd	71
Checkpoint and Restart	rc	cad	2
		ccd	3
Decode URIs	rd	dad	60
		dcd	30
		ded	1
		dgd	1
DRS Supervisor	re	ecd	6
		edd	1
		eed	1
		eid	1
		emd	1
		eod	1
		epd	1
Generate Output	rg	gad	12
		gbd	42
		gcd	19
		gdd	11
		ged	7
		gfd	13
		ghd	7
		gid	11
		gjd	13
		gkd	13
		gld	15
		gmd	16
		gpd	16

Table 2.7.1. JSS Software Hierarchy (Continued)

Set (CPCI)/Group (CPC)	Group (Gr)	Compilation Unit (CU)	Nr. of Modules
		gqd	11
		grd	54
		gsd	8
		gtd	67
		gud	5
		gvd	36
		gwd	29
		tgd	4
Library/Common	rl	lad	1
		lbd	1
		lfd	1
		lhd	1
		lid	1
		lmd	1
		lqd	1
		ltd	1
		lud	1
		lwd	1
Performance and Continuous Evaluation	rp	pad	15
		pbd	18
		pcd	12
		pdd	12
		ped	14
		pgd	77
Select JRT Data	rs	sad	18
		spd	4
Compool		drc	N/A
		Total	1,051
Operating System Set (OSS)			
Radar Data Processor	oa	aaz	26
		acz	1
		aos	1
Card Reader	oc	cap	1
		ccp	1
		cdp	1
		cep	1
		cop	1
Disk	od	dep	1
		wnc	1

Table 2.7.1. JSS Software Hierarchy (Continued)

Set (CPCI)/Group (CPC)	Group (Gr)	Compilation Unit (CU)	Nr. of Modules
OSS Executive	oe	eaz	1
		ebz	1
		ecz	9
		edz	1
		eez	1
		efz	1
		emz	1
		enz	1
		epz	1
		eqz	1
		esz	1
		evz	1
		ewc	1
		ewz	1
		eyz	1
		fmz	1
		mbc	30
CCIU	og	gaz	3
		gbz	3
		gdz	1
		gep	1
		gjz	1
		glz	1
		gpz	1
		grz	1
		gyz	3
Broadcast Controller	oh	hbz	1
ICDD Interface	oi	iaz	1
		iez	1
		ifz	1
		ipz	1
		isz	1
		itz	1
Input/Output	oj	dpp	1
		jax	14
		jbx	1
		jex	1
		jdx	1
		jgx	1
		jox	1
		jzx	1

Table 2.7.1. JSS Software Hierarchy (Continued)

Set (CPCI)/Group (CPC)	Group (Gr)	Compilation Unit (CU)	Nr. of Modules
Dump/Set Memory	ok	kaz	5
		kdx	6
Program Trace	ol	lbx	9
		lcx	1
		lix	1
		lox	2
		lrx	1
		lxx	1
OSS Operator Inputs	om	max	2
		mfx	2
		mgx	8
		mhx	3
		mix	1
		mmx	1
		mnx	8
		mpz	14
		mrx	1
System Confidence	on	cax	3
		cbx	4
		cex	1
		cfx	1
		cgx	1
		chx	1
		cix	1
		clx	1
		cmx	4
		cqx	1
		ctx	1
		cxx	1
		naz	1
		nbh	1
		nbx	1
		nbz	1
		ndz	1
		nhc	1
		nhd	1
		nhh	1
		niz	1
		nkz	1
		nlz	1
		nmz	1
		nnc	1
		nqd	1
		nsz	1

Table 2.7.1. JSS Software Hierarchy (Continued)

Set (CPCI)/Group (CPC)	Group (Gr)	Compilation Unit (CU)	Nr. of Modules
Replay	oo	oaz	1
		orz	12
		osz	6
Recovery	or	rax	4
		rbx	1
		rex	1
OSS Supervisor	os	sas	9
		sbz	26
		scx	3
		sdx	13
		sez	15
		sfx	1
		sfz	1
		six	6
		siz	1
		sjx	1
		sjz	1
		smx	6
		spx	14
		stx	2
		sxx	10
Magnetic Tape	ot	tap	1
		tcp	1
		tep	1
		tfp	1
		tip	1
		tnp	1
		trp	1
		tup	1
		txp	6
Program Trace	ov	vbz	4
		vcz	6
RAT	ow	wac	2
		wic	1
		wiz	8
		wxc	1
CMUX	ox	xaz	1
		xbz	1
		xcc	1
		xcd	1
		xdc	1

Table 2.7.1. JSS Software Hierarchy (Continued)

Set (CPCI)/Group (CPC)	Group (Gr)	Compilation Unit (CU)	Nr. of Modules
		dbs	17
		dgp	1
		dip	1
		dlp	1
		dvp	1
Operator Input Processing	cs	sas	9
Terminal Test	ct	tas	6
Compool		coc	N/A
		mmc	N/A
		Total	557
System Exercise Set (SES)			
Adaptation	ea	aas	29
Control	ec	ccs	10
Display	ed	das	31
		dbs	17
Generate Exercise	eg	gas	43
		gbs	37
		ges	41
List	el	las	41
		lbs	20
		lcs	16
Merge	em	mas	53
Noise File Generation	en	nas	15
Library generation	es	sas	14
Process Inputs	ev	vas	51
		vbs	20
		vcs	27
Compool		sec	N/A
		Total	465

Table 2.7.1. JSS Software Hierarchy (Continued)

Set (CPCI)/Group (CPC)	Group (Gr)	Compilation Unit (CU)	Nr. of Modules
		xez	1
		xgz	1
		xic	1
		xid	2
		xoz	1
		xpz	1
		xtz	1
		xuz	1
		xvz	1
DPS Utilization	oy	dbx	4
		dbz	11
Loader	oz	zrz	9
		ztp	6
		ztz	1
		zup	7
		ldr	13
Safe Data	o1	jad	5
Task Initialization	o2	eah	1
Telling Output	o3	lbz	1
Line Printer	o4	ldp	1
		lep	1
		lip	1
		lkp	1
		lrp	1
System Control Set (SCS)			
Device Status Analysis	ca	aas	13
		cbs	1
		fah	1
Central Computer Input	cc	cas	1
		dap	1
		lap	1
Display Generation	cd	das	2
		dba	9
		dbb	8
		dbf	1

Table 2.7.1. JSS Software Hierarchy (Continued)

Set (CPCI)/Group (CPC)	Group (Gr)	Compilation Unit (CU)	Nr. of Modules
Support Set (SUS)			
Adaptation Calculation	sa	adp	28
Symbolic Library	sb	jol	50
Control	sc	con	116
Compool Data Generator	sd	cdg	10
Symbolic Library	se	csl	57
Symbolic Library	sf	osl	108
Geography Data Generator	sg	gdg	77
File Operations	sm	flo	55
Program Test Aids	sq	pta	38
Recording Specification	sr	rsg	19
System Generation	ss	sgn	1
		sgo	78
		sgp	37
1632 Cross Assembler	sz	asm	57
Compool		ssc	N/A
	Total		731

3. SOFTWARE RELIABILITY MODELS

3.1 Introduction

The purpose of this section is to provide the necessary background information and references to the models used in this study, and to explain what modifications (if any) have been made in the models to accommodate the circumstances surrounding the JSS database. Comments concerning the model assumptions in relation to the JSS database will also be made in each case.

Final subsections have been included which contain observations concerning similarities which exist among the models in their original forms, and comments on their applicability, in general, to the JSS database. Also included is a commentary on the methods of parameter estimation advocated for each model. The last subsection provides rationale for choosing a measure derivable from each model's outputs which would assist project office personnel in adequately monitoring the formal and qualification testing efforts of a software development project.

3.2 Imperfect Debugging Model

The Imperfect Debugging Model was developed by Goel & Okumoto (Goel, 1978; Goel & Okumoto, 1978) in response to the need for a software reliability model which would model the phenomenon of uncertainty in error removal/correction in software debugging. Some of the major assumptions of this model are listed below in direct quotation from Goel & Okumoto (1978):

"(i) The error causing a software failue, when detected, is corrected with probability $p(0 \leq p \leq 1)$, while with probability $q(p + q = 1)$ we fail to completely remove it. Thus, q is the probability of imperfect debugging.

(ii) Errors in the software package are independent of each other and have a constant occurrence rate.

(iii) The probability of two or more errors occurring simultaneously is negigible.

(iv) The time to remove an error is considered to be negligible in this model.

(v) No new errors are introduced during the debugging process.

(vi) At most one error is removed at correction time."

In addition, it is assumed that $X(t)$, the number of errors remaining in the system at time t (the authors do not specify how t is measured, i.e., calendar time, execution time, CPU time, etc.) is a semi-Markov process with initial value $X(0)=N$. The sojourn times in each state are additionally assumed to be exponentially distributed with failure rate proportional to the number of errors remaining in the software.

To aid in understanding this process governing the number of errors remaining in the software, and to help in explaining the modifications to this model which are necessary to accommodate the JSS data, it is instructive to describe the evolution of the process in a qualitative fashion. At time $t=0$, there are N errors in the software. After S_1 units of time (where S_1 is exponentially distributed with failure rate $N\lambda$) an error manifests itself. With probability p (independent of S_1) this error is removed instantaneously and with probability $q=1-p$, the error is not removed. If the error was removed, then S_2 time units later (where S_2 is independent of S_1, and is exponentially distributed with failure rate $(N-1)\lambda$) the next error manifests itself, and is instantaneously removed with probability p, and not removed with probability q. If the first error had not been removed, then S_2^* time units later (where now S_2^* is exponentially distributed with failure rate $N\lambda$) the next error (which could possibly be the first error again) manifests itself, and is instantaneously removed with probability p, and not removed with probability q. The process proceeds in this fashion until all errors are removed, which will ultimately happen as long as $0 < p \leq 1$, and $\lambda > 0$.

Goel (1978), and Goel & Okumoto (1978) have provided methodologies for estimating the unknown quantities N, λ , and p based on knowing the successive times between software error manifestations along with corresponding variables taking value 1 if the corresponding error was due to imperfect debugging, and 0 otherwise. In addition, the authors have provided a rather exhaustive analysis of this model in terms of the probability distribution of the amount of time to achieve a specified number of errors, distribution of number of remaining errors, and expected number of errors detected and remaining. Many of the expressions derived in Goel (1978) and Goel & Okumoto (1978) were subsequently simplified in Shanthikumar (1980) and independently in James et. al. (1982).

The assumptions quoted previously, and the method of parameter estimation discussed herein deserve comment in the context of the JSS data. While assumptions i, iii, and iv are plausible for the JSS data, assumptions ii, v, and vi probably do not hold. Many of the JSS program personnel concur that errors do not individually possess a constant occurrence rate, and they usually cite examples relating to errors existing in portions of the software which are infrequently exercised. Moreover, Nagel & Skrivkan (1982, p.63) offer convincing experimental evidence to

this effect. They also offer evidence which would tend to support the assumptions relating to exponential sojourn times, provided that time is measured in the proper unit (e.g. run time, execution time). It is doubtful in view of the varying manpower, scheduling, and other factors that calendar time would be an adequate measure of time on JSS.

Finally, the most serious barrier to fitting this model to the JSS data is the unavailability of time-between-errors data. This data is unavailable in any reliable form on JSS because PTRs are not written and dated necessarily on the day the error occurred. Moreover, the best resolution in such data would be to the nearest day which would lead to "ties" in the input data which according to the model, are impossible. Another difficulty is that testing (even at the module level) does not cease when an error is detected, and errors are not necessarily removed (or attempts to remove made) when the errors are detected. In some cases, an error is not removed until days or weeks after it was detected.

To alleviate some of these difficulties and allow some form of the Imperfect Debugging Model to be utilized (however modified) on the JSS data, it is instructive to consider what happens if all the assumptions of the Imperfect Debugging Model are assumed to hold, but that the observations are sampled in a different way (i.e., different than observing the times between each error manifestation and whether or not the error was due to imperfect debugging). In particular, consider the sequence of times between error manifestations in which the errors are actually <u>removed</u>. Denote these times by $T_1, T_2, \ldots T_N$. Let us first consider the distribution of T_1.

The first error manifestation occurs at a time which is exponentially distributed with failure rate $N\lambda$. However, this is not equal to T_1 unless the error is removed, which happens with probability $\bar{p}$. If it is not removed, then a time later (which is independent, and identically distributed as the time to the first manifestation) the second manifestation occurs. If the bug is removed, then T_1 is the sum of two independent and identically distributed exponential random variables with failure rate $N\lambda$. If it is not removed, another period of time which is independent and identically distributed to the first two time periods elapses until the third manifestation. If the error is removed on this third try, then T_1 is the sum of three independent and identically distributed exponential random variables with failure rate $N\lambda$. Proceeding in this fashion, it is easy to see that T_1 has the same distribution as the random sum

$$\sum_{i=1}^{L} X_i$$

where X_1, X_2,... are independent and identically distributed exponential random variables with failure rate $N\lambda$, and L is a random integer valued variable independent of the X_i and having the geometric probability distribution

$$P\{L=j\} = q^{j-1}p;\ j=1,2,\ \ldots\ .$$

It is well-known that such a geometric convolution of exponential random variables is again, exponentially distributed with failure rate $N\lambda p$. To see this, note that the characteristic function of X_j is;

$$E[\exp(itX_j)] = N\lambda/(N\lambda - it)$$

where $i = \sqrt{-1}$.

Therefore, the characteristic function of

$$\sum_{k=1}^{L} X_k$$

is equal to

$$E[\exp(it \sum_{k=1}^{L} X_k)] = p\sum_{k=1}^{\infty} q^{k-1} \left[\frac{N\lambda}{N\lambda - it}\right]^k$$

$$= \frac{Np\lambda}{(Np\lambda - it)}$$

which is the characteristic function of an exponentially distributed random variable with failure rate $Np\lambda$. That is, T_1 is exponentially distributed with failure rate $N\lambda p$. In general, it can be shown using similar arguments that T_i is exponentially distributed with failure rate $(N-i+1)\lambda p$, $1 \leq i \leq N$. The implication here is obvious: T_1, T_2, ..., T_N constitute the observations in a Jelinski-Moranda (Moranda, 1975, p. 328) De-Eutrophication Model with $\phi = \lambda p$.

In terms of fitting the Imperfect Debugging Model to the JSS database, it is true, roughly speaking, that if only those errors which are actually removed are considered, then the Jelinski-Moranda model (or some variant designed to handle grouped data) can be fit. In other words, the two models are indistinguishable under this type of sampling plan. Luckily, Lipow (1974) proposed an extension of the Jelinski-Moranda Model which was based on the same assumptions as the original Jelinski-Moranda Model, but which was based on grouped input data as is available on JSS. Subsequently, in Schafer et.al. (1979, p.3-2) a further extension whereby the actual number of errors removed at the end

of each time interval could be used was developed for use on data from other Hughes projects. It is this version which is used in place of the Imperfect Debugging Model on the JSS data.

The assumptions underlying this model (subsequently referred to as the Jelinski-Moranda model) are slightly less restrictive than those of the Imperfect Debugging Model. Assumption (ii) from Goel & Okumoto (1978) holds, except due to the possibility of imperfect debugging, the parameter λ is replaced by $\phi = \lambda p$. Assumptions (iii), (iv), and (v) also hold. It is further assumed that at the end of a debugging-time interval a number of errors are removed and that no errors are removed during the time interval. It is also assumed that in an interval of time, the number of errors detected will be Poisson distributed with mean proportional to the number of errors remaining in the software. The details of this model may be found in Schafer et.al. (1979). The initial number of errors N , and the parameter ϕ are estimated by solving the following two equations iteratively for N and ϕ:

$$\sum_{i=1}^{k} \frac{N_i}{N-M_{i-1}} - \phi \sum_{i=1}^{k} \tau_i = 0 \qquad (3.2.1)$$

$$\frac{1}{\phi} \sum_{i=1}^{k} N_i - \sum_{i=1}^{k} (N-M_{i-1}) \tau_i = 0 \qquad (3.2.2)$$

where M_j is the total number of errors removed up to the end of the jth time interval, τ_j is the length of the jth time interval, N_j is the number of errors detected in time interval τ_j, and k is the total number of time intervals observed. The method of solving (3.2.1) and (3.2.2) is that of Newton-Raphson (after algebraically, eliminating ϕ) as described in Appendix B.

In summary of this section it is important to review several key points. First, we are not saying that the Imperfect Debugging Model is generally equivalent to the Jelinski-Moranda model. The fact is, that under a sampling plan which only considers removed errors, the statistical analysis of the two models is the same. Worded differently, under this type of sampling plan, the Imperfect Debugging Model <u>reduces</u> to the Jelinski-Moranda Model.

Secondly, since only grouped data is available on JSS, we could not utilize the Imperfect Debugging Model in its original form. We therefore chose to fit the version of the Jelinski-Moranda Model developed in Lipow (1974) and extended in Schafer et.al. (1979) since it embodies the essential assumptions of the Imperfect Debugging Model. For the purpose of this study, when we refer to the Jelenski-Moranda Model, we will be referring to the version studied in Schafer, et.al. (1979).

3.3 Nonhomogeneous Poisson Model

The Nonhomogeneous Poisson Model (Goel & Okumoto, 1980) was a pioneering effort in the application of Nonhomogeneous Poisson process modelling to software. This model assumes that the cumulative number of software errors detected in the time (again, time units are unspecified by the authors) from zero to t follows a Nonhomogeneous Poisson process with mean value function

$$m(t) = a(1-\exp(-bt)) \qquad (3.3.1)$$

where a and b are positive. Rosner (1965) proposed a very similar model for hardware reliability growth. Rosner's model was subsequently studied in Schafer, et.al. (1975), and referred to as the "IBM Model". This model assumed that the cumulative expected number of failures up to time t was given by

$$V(t) = \lambda t + K_1 (1-\exp(-K_2 t)) \qquad (3.3.2)$$

where λ, K_1, and K_2 are positive constants.

Obviously, (3.3.2) reduces to (3.3.1) when $\lambda = 0$.

The specific assumptions underlying the Nonhomogeneous Poisson Model are simple and unrestrictive (Goel & Okumoto, 1980):

(1) "... the usage of the system is basically similar over time."

(2) "... the number of failures in $(t, t+\Delta t)$ is [roughly] proportional to the number of undetected errors at [time] t..."

Assumptions (1) and (2) above were given in the context of deriving (3.3.1) as a <u>deterministic</u> model for software errors. Subsequently, the authors impose the Nonhomogeneous Poisson structure to account for random deviations from (3.3.1). In this connection, they also point out a third assumption: (3) "... a detected error may not be removed and as a result may cause additional failure(s) at a later stage. For the N(t) process, such occurrences are counted as new events."

In (3), N(t) is the random cumulative number of errors detected by time t.

Assumption (3) is plausible for the JSS data, while assumption (1) (and hence assumption (2)) are probably not true uniformly over all of the JSS database. The evidence of this is obvious upon inspecting the plots of observed cumulative PTR's

versus time in Section 3.9. These plots all show evidence of alternating increasing and decreasing error rate which is inconsistent with (3.3.1) whose error rate is given by

$$abexp(-bt)$$

which is always decreasing in time. Possible remedies to this situation with respect to the JSS database are to restrict attention to single Compilation Unit (and thus eliminate the effects of software build-up) and to single test phases (to eliminate the effects of nonhomogeneity of testing). Further discussion on this matter is contained in Section 3.9 and Section 4.

The procedure for fitting this model is given in Goel & Okumoto (1980, pp.25-27). Briefly, the parameters a and b are estimated by solving:

$$a\,(1-\exp(-bt_n)) = y_n \qquad (3.3.3)$$

$$at_n e^{-bt_n} = \sum_{i=1}^{n} \frac{(y_i-y_{i-1})(t_i e^{-bt_i} - t_{i-1}e^{-bt_{i-1}})}{e^{-bt_i} - e^{-bt_{i-1}}} \qquad (3.3.4)$$

for a and b. In (3.3.3) and (3.3.4), y_i errors have been detected by time t_i, $1 \leq i \leq n$, and the Newton-Raphson iterative procedure is used after algebraic elimination of a (See Appendix B).

3.4 <u>IBM Poisson Model</u> The IBM Poisson Model is documented in Brooks and Motley (1980). It is a generalization of the Jelinski-Moranda model in the following respects:

(1) It recognizes and attempts to account for software build-up during testing.

(2) It recognizes and attempts to account for the insertion of errors during the correction process.

(3) It allows data from several different groups of modules to be used simultaneously to estimate the unknown parameters.

(4) It utilizes grouped data as is available on the JSS project.

The essence of the model remains in close accord with the original Jelinski-Moranda model. That is, the basic assumptions are that software errors are independent of one another and occur

with equal probability (an assumption convincingly discounted by Nagel and Skrivan (1982)), and that the number of errors occurring in an interval of testing time is Poisson distributed with mean proportional to the number of errors "at risk" at the beginning of the time interval (this is, in a sense, the number of errors remaining). As usual, N initial errors are assumed present before testing begins. An added assumption is that the number of errors inserted on any occasion is proportional to the number of errors detected. These assumptions are explicitly given in Brooks and Motley (1980). Assumptions implicit in their mathematical derivation are explained below.

First, the number of errors at risk on test occasion i is

$$\overline{N_i} = f_i N - \alpha Q_i \qquad (3.4.1)$$

where f_i is the fraction of the system which is under test, Q_i is the number of errors detected in that portion of the system under test prior to the ith test occasion. Here, f_i is assumed known, and Q_i is observed. The parameter α is the "... probability of correcting errors in the system without reinserting additional errors and exposing others to discovery. (Brooks and Motley, 1980, p.2-11)." Of course, like N, α must be estimated from data.

The second tacit assumption is that no errors are removed during a unit-test time interval (only at the end of such periods).

With respect to the JSS data the IBM Poisson Model is most suitably applied at the CU level since the values f_i in (3.4.1) are not known for JSS. By considering the individual CU as a system, it can be assumed that $f_i = 1$ for all i. The assumption embodied in (3.4.1) is questionable for JSS. In fact, it was possible on JSS to observe exactly how many errors had been removed prior to each occasion. This quantity is related to M_i defined in Section 3.2, i.e., M_{i-1} is the number of errors removed prior to the beginning of the <u>ith</u> time interval. Since this data is available on JSS, it seemed inefficient to estimate it by αQ_i as is done in (3.4.1). Therefore, we considered two versions of the IBM Poisson Model. The first version has αQ_i in (3.4.1) replaced by M_{i-1}, and thus eliminates the need to estimate α. The second version is exactly the IBM Poisson Model as described by the authors. In the first version of the IBM Poisson Model, the unknowns N and ϕ are estimated by solving (for N and ϕ) the equations

$$\sum_{i=1}^{k} \left(\frac{N_i}{\overline{N_i}} - \{1-(1-\phi)^{\tau_i}\} \right) = 0 \qquad (3.4.2)$$

$$\sum_{i=1}^{k} \tau_i(1-\phi)^{\tau_i - 1}\left[\frac{N_i}{1-(1-\phi)^{\tau_i}} - \bar{N}_i\right] = 0 \quad (3.4.3)$$

where $\bar{N}_i = N - M_{i-1}$, τ_i is the length of the $i^{\underline{th}}$ test occasion, N_i is the number of errors detected during the $i^{\underline{th}}$ test occasion, and k is the total number of test occasions.

In the second version we considered the exact model as presented in Brooks and Motley (1980, p.2-21). This becomes a three parameter model with the parameters estimated by solving the equations (for ϕ, N and α):

$$\sum_{i=1}^{k}\left(\frac{N_i}{\bar{N}_i} - \{1-(1-\phi)^{\tau_i}\}\right) = 0 \quad (3.4.4)$$

$$\sum_{i=1}^{k} \tau_i(1-\phi)^{\tau_i - 1}\left[\frac{N_i}{1-(1-\phi)^{\tau_i}} - \bar{N}_i\right] = 0 \quad (3.4.5)$$

$$\sum_{i=1}^{k}\left(\sum_{j=1}^{i-1} N_j\right)\left(\frac{N_i}{\bar{N}_i} - \{1-(1-\phi)^{\tau_i}\}\right) = 0 \quad (3.4.6)$$

where $\bar{N}_i = N - \alpha \sum_{j=1}^{i-1} N_j$,

and $\sum_{j=1}^{i-1} N_j$ is defined to be zero when i=1.

As usual, the Newton-Raphson iterative procedure was used to solve (3.4.2) through (3.4.6) after algebraically eliminating N (See Appendix B).

3.5 Generalized Poisson Model The Generalized Poisson Model (GPM) is an extension of the Jelinski-Moranda model, and was proposed in Schafer, et.al. (1979) for two purposes; to generalize the assumption of exponential times between software error detections to Weibull distributions, and to provide a model whose input data requirements would match the data available on Hughes' and other software development projects. The GPM assumes that the number of errors detected during the $i^{\underline{th}}$ debugging time interval of length τ_i has a Poisson distribution with mean

$$\phi(N-M_{i-1})\tau_i^{\alpha} \tag{3.5.1}$$

where ϕ is a constant of proportionality, N is the total number of errors present in the software initially, and M_j is the total number of errors removed up to the end of the $j^{\underline{th}}$ debugging time interval. It is further assumed that when errors are removed, they are removed at the ends of the debugging-time intervals. In this model, like the previous models, the authors do not specify the units of time measurement except insofar as they be "debugging-time" units.

In order to fit this model the authors propose that the following three equations be solved simultaneously for α, N, and ϕ based on k debugging time intervals:

$$\sum_{i=1}^{k} \frac{N_i}{N-M_{i-1}} = \phi \sum_{i=1}^{k} \tau_i^{\alpha} \tag{3.5.2}$$

$$\frac{1}{\phi} \sum_{i=1}^{k} N_i = \sum_{i=1}^{k} (N-M_{i-1})\tau_i^{\alpha} \tag{3.5.3}$$

$$\sum_{i=1}^{k} N_i \ln\tau_i = \phi \sum_{i=1}^{k} (N-M_{i-1})\tau_i^{\alpha} \ln\tau_i \tag{3.5.4}$$

The computerized solution of these equations is based on two-parameter Newton-Raphson iteration after algebraic elimination of ϕ.

In Schafer et.al. (1979) substantial difficulties with the solution of (3.5.2) - (3.5.4) along with generally poor fits were reported for the GPM. However, in that investigation, the GPM was still judged to fit better than the other models studied (which included the Jelinski-Moranda, Schick-Wolverton, and Non-homogeneous Poisson Model). In that investigation, no effort was made to restrict attention to single CU or test phases and thus the effects of software build-up and variable test phases were included in the data.

3.6 Geometric Poisson Model

The Geometric Poisson Model is presented in Moranda (1975) in two versions; one based on knowing the times between successive software error detections, and the other based on the numbers of errors detected in successive equal time periods (as usual, the author does not specify how time is measured).

For the JSS data, the second version of this model must be considered since the times between error detections are not available. In this second version, the number of errors detected in the i^{th} time interval is Poisson distributed with mean

$$\lambda K^{i-1},\ i=1,2,\ldots \tag{3.6.1}$$

where $\lambda > 0$ and $0 < K < 1$.
Note that (3.6.1) is independent of the time interval length as would be expected when all such intervals are of the same length. On the JSS database, it is more convenient to consider time intervals of different lengths. When this model is applied to time intervals of variable length, the estimates of λ and K in (3.6.1) become solutions to

$$\sum_{i=1}^{k} \left\{ \frac{N_i}{\lambda} - K^{t_{i-1}} \left[\frac{1-K^{\tau_i}}{1-K} \right] \right\} = 0 \tag{3.6.2}$$

$$\sum_{i=1}^{k} \left(\frac{N_i Q_i'}{Q_i} - \lambda Q'_i \right) = 0 \tag{3.6.3}$$

where N_i is the number of errors detected in the interval of length τ_i, $t_i = \sum_{j=1}^{i} \tau_j$ ($t_0 = 0$), k is the number of intervals, and

$$Q_i = K^{t_{i-1}}\left[\frac{1-K^{\tau_i}}{1-K}\right]$$

$$Q_i' = K^{t_{i-1}}\left[\frac{(1-K^{\tau_i})-\tau_i K^{\tau_i-1}(1-K)}{(1-K)^2}\right] + \frac{t_{i-1}Q_i}{K}.$$

Equations (3.6.2) and (3.6.3) result from differentiating the log-likelihood function

$$\sum_{i=1}^{k}\left[N_i \log \lambda_i - \lambda_i - \log (N_i!)\right] \qquad (3.6.4)$$

with respect to λ, and K, and setting the resulting equations equal to zero. In (3.6.4), λ_i is the expected number of errors detected in time interval i of length τ_i. To see how the original Geometric Poisson model leads to this model for unequal time intervals, notice that from Moranda (1975), the expected number of errors in the first τ_1 units of time is

$$\lambda + \lambda K + \cdots + \lambda K^{\tau_1 - 1} = \lambda\left[\frac{1-K^{\tau_1}}{1-K}\right]$$

The expected number of errors in the second time interval of length τ_2 is

$$\lambda K^{\tau_1} + \lambda K^{\tau_1+1} + \cdots + \lambda K^{\tau_1+\tau_2-1} = \lambda K^{\tau_1}\left[\frac{1-K^{\tau_2}}{1-K}\right]$$

In general, the expected number of errors in the i^{th} time interval of length τ_i is

$$\lambda K^{t_{i-1}} + \lambda K^{t_{i-1}+1} + \dots + \lambda K^{t_{i-1}+\tau_i-1} = \lambda K^{t_{i-1}} \left[\frac{1-K^{\tau_i}}{1-K}\right].$$

Equations (3.6.2) and (3.6.3) reduce to equations (11) and (12) in Moranda (1975) when $\tau_i = 1$, $1 \leq i \leq k$ (with obvious changes in notation).

Equations (3.6.2) and (3.6.3) are solved for λ and K by algebraically eliminating λ and then applying Newton-Raphson iteration (See Appendix B).

For purposes of comparison of the models, it is necessary to derive an expression for the total expected number of errors present initially under this model (analogous to N in the IBM Poisson, GPM, Binomial, Imperfect Debugging, or "a" in the Nonhomogeneous Poisson Model). This quantity is easily derived from this model by noting that the expected number of errors detectable in an infinite number of unit time intervals is

$$\sum_{i=1}^{\infty} \lambda K^{i-1} = \frac{\lambda}{1-K}.$$

In the context of the Geometric Poisson Model we will define

$$N = \lambda/(1-K)$$

for purposes of comparison to the other models.

3.7 Binomial Model

The Binomial Model, like the GPM, was introduced in Schafer, et.al. (1979). This model is based on observing successive numbers of errors in successive time intervals (time units not specified). The distributional assumptions are that the conditional distribution of N_i given $N_1, N_2, \dots, N_{i-1}$, is binomial with parameters

$$N - \sum_{j=1}^{i-1} N_j$$

and $p_j = 1-e^{-a\tau_j}$ where N is the number of initial errors, and N_i is the number of errors detected in the time interval of length τ_i. Thus, the expected number of errors detected in time interval τ_i is

$$(N-\sum_{j=1}^{i-1} N_j)(1-e^{-a\tau_i}) \tag{3.7.1}$$

where, as usual, the summation in (3.7.1) is defined to be zero when i=1.

In Schafer et.al. (1979), it was recommended that the estimates of N and a be obtained using a least squares technique, i.e., by minimizing

$$\sum_{i=1}^{k}\left[N_i - (1-e^{-a\tau_i})(N-\sum_{j=1}^{i-1} N_j)\right]^2 .$$

This led the authors to define the estimates of a and N to be solutions to

$$\sum_{i=1}^{k} N_i(1-e^{a\tau_i}) = \sum_{i=1}^{k} (N-M_{i-1})(1-e^{-a\tau_i})^2 \tag{3.7.2}$$

$$\sum_{i=1}^{k} N_i\tau_i(N-M_{i-1})e^{-a\tau_i} = \sum_{i=1}^{k} \tau_i(N-M_{i-1})^2(1-e^{-a\tau_i})e^{-a\tau_i} \tag{3.7.3}$$

Equations (3.7.2) and (3.7.3) are solved iteratively using Newton-Raphson techniques (See Appendix B).

3.8 Similarities Among the Models

There are some striking similarities among the software models under investigation in this study. In fact, they all possess striking similarity to the Jelinski-Moranda model, in one form or another. For example, in Section 3.2, it was shown that under a sampling plan which considers only removed errors, the Imperfect Debugging Model actually reduces to the original Jelinski-Moranda De-Eutrophication Model.

The Geometric Poisson Model appears, on the surface, to possess many different qualities. However, the models are really quite similar as the following argument will show. Under the extension of the Jelinski-Moranda model proposed by Lipow (1974) (and derived entirely within the assumptions of the Jelinski-Moranda model except for the added assumption that the errors are removed at the end of each time period) the expected numbers of errors to occur in the first, second, third, etc., debugging time intervals are

$$
\begin{aligned}
&\text{1st interval: } \phi N \tau_1 \\
&\text{2nd interval: } \phi(N-N_1)\tau_2 \\
&\text{3rd interval: } \phi(N-N_1-N_2)\tau_3 \\
&\quad\vdots \\
&i^{\text{th}} \text{ interval: } \phi\left(N-\sum_{j=1}^{i-1} N_j\right)\tau_i
\end{aligned}
\tag{3.8.1}
$$

and so on, where N_i is the number of errors detected during the i^{th} interval. The first step to reduce this scenario to that of the Geometric Poisson is to assume (for the moment) that $\tau_i=1$, for all i. Strictly speaking, the values in 3.8.1 are <u>conditional expectations</u>; conditioned on the past observations. The Geometric Poisson Model simply uses the unconditional expectations of the expressions in (3.8.1) to account for the possibility that not all of (or possibly more than) the N_i errors observed in a time interval are actually removed. Thus, for the Geometric Poisson Model, the expected (unconditional) number of errors to occur in the second interval is

$$(N - \phi N) = N(1-\phi);$$

the expected number to occur in the third interval is

$$(N - \phi N - \phi N(1-\phi)) = N(1-\phi)^2;$$

and so on. The expected (unconditional) number of errors in the i^{th} interval is simply

$$(\phi N)(1-\phi)^{i-1}$$

which is exactly the Geometric Poisson Mean value function with (see Section 3.6) $\lambda = \phi N$ and $K = 1-\phi$.

The Nonhomogeneous Poisson model may be thought of as a continuous analog to the Jelinski-Moranda model in the sense that the mean value functions are based on similar principles. That is, for the mean value function of the Nonhomogeneous Poisson, $m(t)$, it is assumed that for constants $a > 0$, and $b > 0$,

$$m(t+h)-m(t) \cong b(m(\infty)-m(t))h$$

i.e., the expected number of errors in the interval of time from t to t+h is proportional (approximately, for small h) to the number of error remaining (expected) at time t. This is exactly the Jelinski-Moranda "principle". An even more striking resemblance occurs with the Geometric Poisson Model. Assuming for the moment that all time intervals are of width one unit, the expected number of errors in interval i is, according to the Geometric Poisson Model,

$$\lambda K^{i-1} \qquad (3.8.2)$$

and, for the Nonhomogeneous Poisson Model,

$$a(\exp(-b(i-1))-\exp(-bi)) \qquad (3.8.3)$$

But, notice that

$$a(e^{-b(i-1)}-e^{-bi}) = \left[\frac{ae^b}{e^b-1}\right](e^{-b})^{i-1}$$

which is exactly (3.8.2) with

$$\lambda = ae^b/(e^b-1) \text{ and } K=e^{-b}.$$

Going one step further, in the Geometric Poisson Model with unequal time intervals of integer length, the expected number of errors in the i^{th} time interval of length τ_i time units is

$$\lambda K^{t_{i-1}} + \lambda K^{t_{i-1}+1} + \cdots + \lambda K^{t_{i-1}+\tau_i-1} \qquad (3.8.4)$$

where $t_i = \Sigma_{j=1}^{i}\tau_j$ ($t_0 = 0$). For the Nonhomogeneous Poisson Model, the expected number of errors to occur in the $i^{\underline{th}}$ interval of length $\tau_i = t_i - t_{i-1}$,

is

$$a(e^{-bt_{i-1}} - e^{-bt_i}) \qquad (3.8.5)$$

Notice that (3.8.4) may be rewritten as

$$\left(\frac{\lambda}{1-K}\right)\left(e^{t_{i-1}\ell nK} - e^{t_i \ell nK}\right)$$

which is exactly (3.8.5) with $a = \lambda/(1-K)$, and $b = -\ln K$, or solving for λ and K, $\lambda = ae^b/(e^b-1)$ and $K = e^{-b}$, just as in the case of equal time intervals. We may thus conjecture now that the Geometric Poisson Model and the Nonhomogeneous Poisson Model will give the same results for a and b (or λ and K) under the reparametrization

$$\begin{aligned} a &= \lambda/(1-K) \\ b &= -\ln K \end{aligned} \qquad (3.8.6)$$

when the time intervals are of integer length.

The similarities between the IBM Poisson and the Jelinski-Moranda Models are spelled out in Brooks & Motley (1980), while the similarities between the GPM and the Jelinski-Moranda model are pointed out in Schafer et.al. (1979).

The Binomial Model is also seen to be similar to the Jelinski-Moranda model by comparing mean value functions. For the Binomial Model, the expected number (conditional) of errors to be detected during the $i^{\underline{th}}$ interval of length τ_i is

$$(N - \sum_{j=1}^{i-1} N_j)(1-\exp(-a\tau_i)) \qquad (3.8.7)$$

Using the approximation $1-\exp(-h) \approx h$ when h is close to zero, (3.8.7) can be approximated by

$$a\,\tau_i\,(N - \sum_{j=1}^{i-1} N_j)$$

which is exactly given in (3.8.1) (when ϕ=a) for the Jelinski-Moranda Model. Moreover, when a τ_i is small for each i, and N very large, the binomial distribution is approximated by the Poisson for each time interval, completing the analogy between the two models.

To summarize, it may be conjectured that when all models are seen to fit a particular software error dataset, the estimates of the initial number of errors (or the analogous quantity) should be very close, as should be the estimates of the "ϕ" parameter except for the parameter ϕ in the Generalized Poission Model. To facilitate these comparisons in subsequent analyses, the model parameters in each case can be translated into N and ϕ according to Table 3.8.1.

Table 3.8.1

Parameter Translations Relating to the Jelinski-Moranda Model

Model/ Parameters	Formula For: N	Formula For: ϕ	Comment
Geometric Poisson λ , K	$\lambda/(1-K)$	1-K	$\lambda/(1-K)$ is the expected number of errors in infinite time
Jelinski-Moranda N, ϕ	N	ϕ	
Nonhomogeneous Poisson a, b	a	b	a is the expected number of errors in infinite time.
Generalized Poisson N, ϕ , α	N	ϕ	This value of ϕ will not be comparable to the other models due to the parameter α
IBM Poisson N, ϕ , α	N	ϕ	
Binomial N, a	N	a	

3.9 Applicability of the Models to the JSS Database

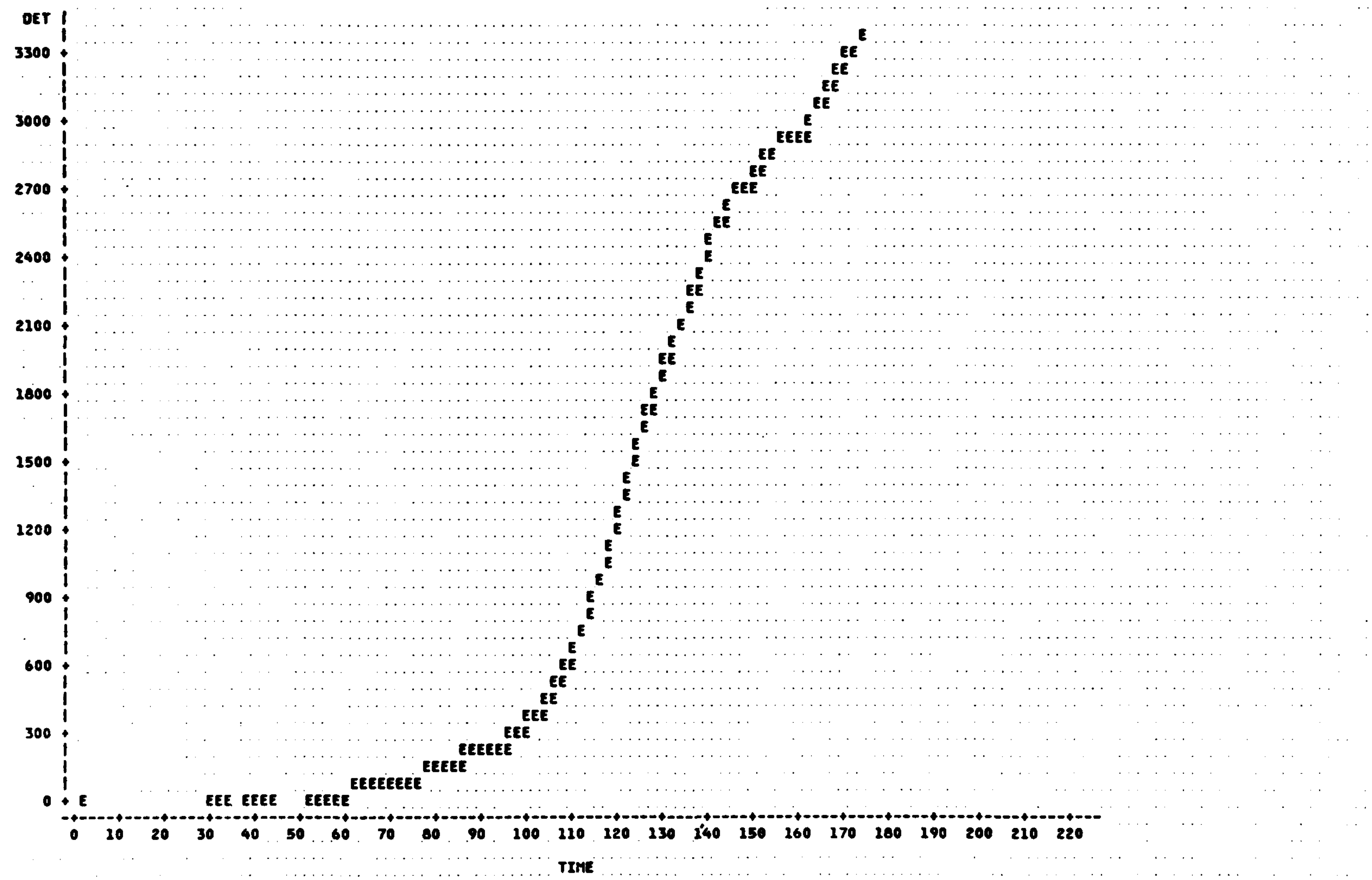
There is no way to absolutely prove or disprove the validity of all the software reliability models' assumptions in relation to the JSS database. Some of the assumptions are obviously not satisfied (e.g. that no new errors are introduced during the debugging process, or that at most one error is removed at correction time), while others are plausible, but not verifiable absolutely (e.g. that the times between software error occurrences are exponentially distributed, or that the number of errors in a fixed interval of time is Poisson distributed). Other assumptions have been shown "statistically" to be untrue for software in general (e.g. that all errors have the same constant rate of occurrence; see Nagel and Skrivan (1982)). Moreover, with the variability of total manpower effort, the software build-up during testing, and the variability of test phase, it should not be expected that any of the models would fit the JSS database over all. To illustrate the reason for this, Figures 3.9.1 through 3.9.12 show the cumulative number of errors detected for the six CPCIs, and the cumulative number of errors removed for the six CPCIs as a function of (calendar) time. The effects of variability in manpower effort, software build-up, and test phase are possibly manifested as changes in inflection in these plots. All of the software reliability models would predict a cumulative error detected curve which is concave downward everywhere, i.e. a decreasing error rate everywhere. The curves in Figures 3.9.1 through 3.9.12 show regions (often more than one) of increasing error rate.

At this point it is tempting to conclude that the models do not fit the JSS database. Indeed, not much attention has been given to such details as varying manpower effort, test phase, and software build-up (except for Brooks and Motley (1980)). As mentioned earlier, Goel (1980, p.43) apparently observed the phenomenon of a transient increasing error rate in his database when fitting the Nonhomogeneous Poisson Model and found it necessary to censor his first nine weeks of data because, as he states, they were "... interested in analyzing the software failures over the period when they are decreasing." As seen in Figures 3.9.1 through 3.9.6, there can be more than one distinct period of software error rate decrease, in general.

It is conceivable (even obvious in some cases) that test phase transitions can cause changes in the rate of error detection. It is also obvious that software build-up also effects the rate of error detection. Therefore, in order to apply the software reliability models to the JSS database with any degree of success, it is necessary to apply the models to a given compilation unit (CU) and a given test phase. By restricting attention to a given CU, the software build-up problem is reduced since all the software in a CU enters configuration control at once. Also,

FIGURE 3.9.1
APS

CUMULATIVE ERRORS DETECTED VS TIME



NOTE: 29 OBS HIDDEN

FIGURE 3.9.2
DIS

CUMULATIVE ERRORS DETECTED VS TIME

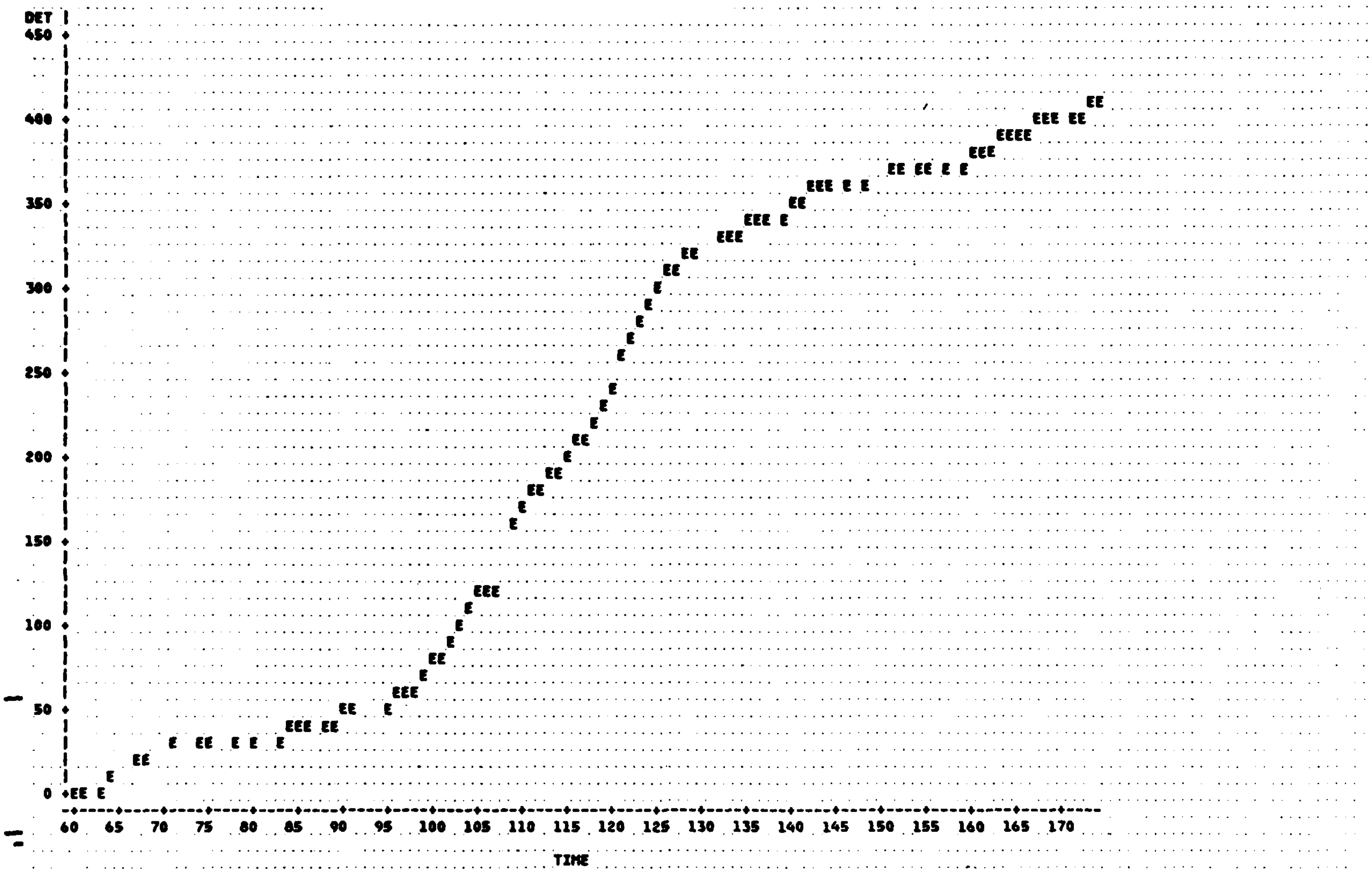


FIGURE 3.9.3
DRS
CUMULATIVE ERRORS DETECTED VS TIME

PLOT OF DET*TIME   SYMBOL USED IS E

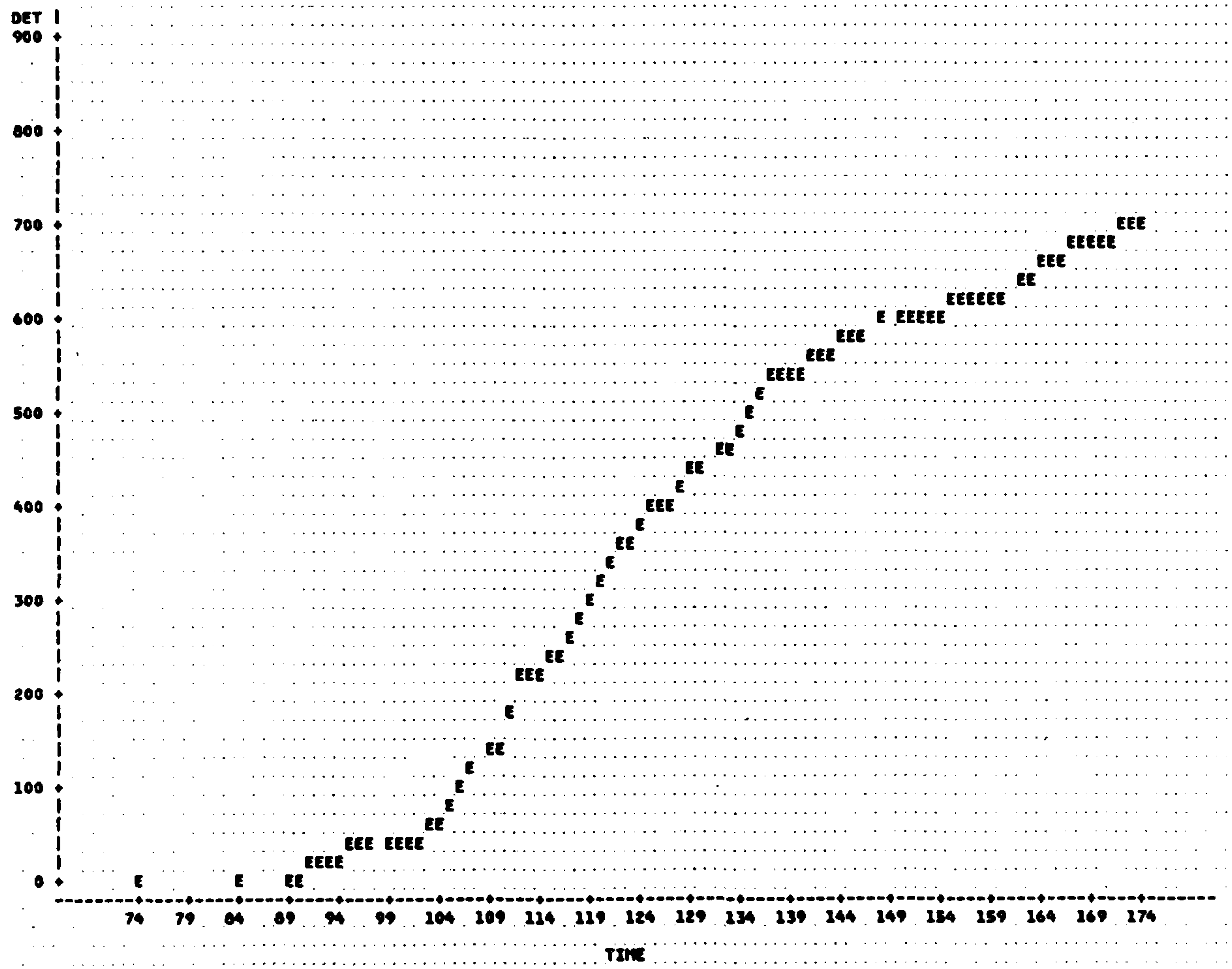
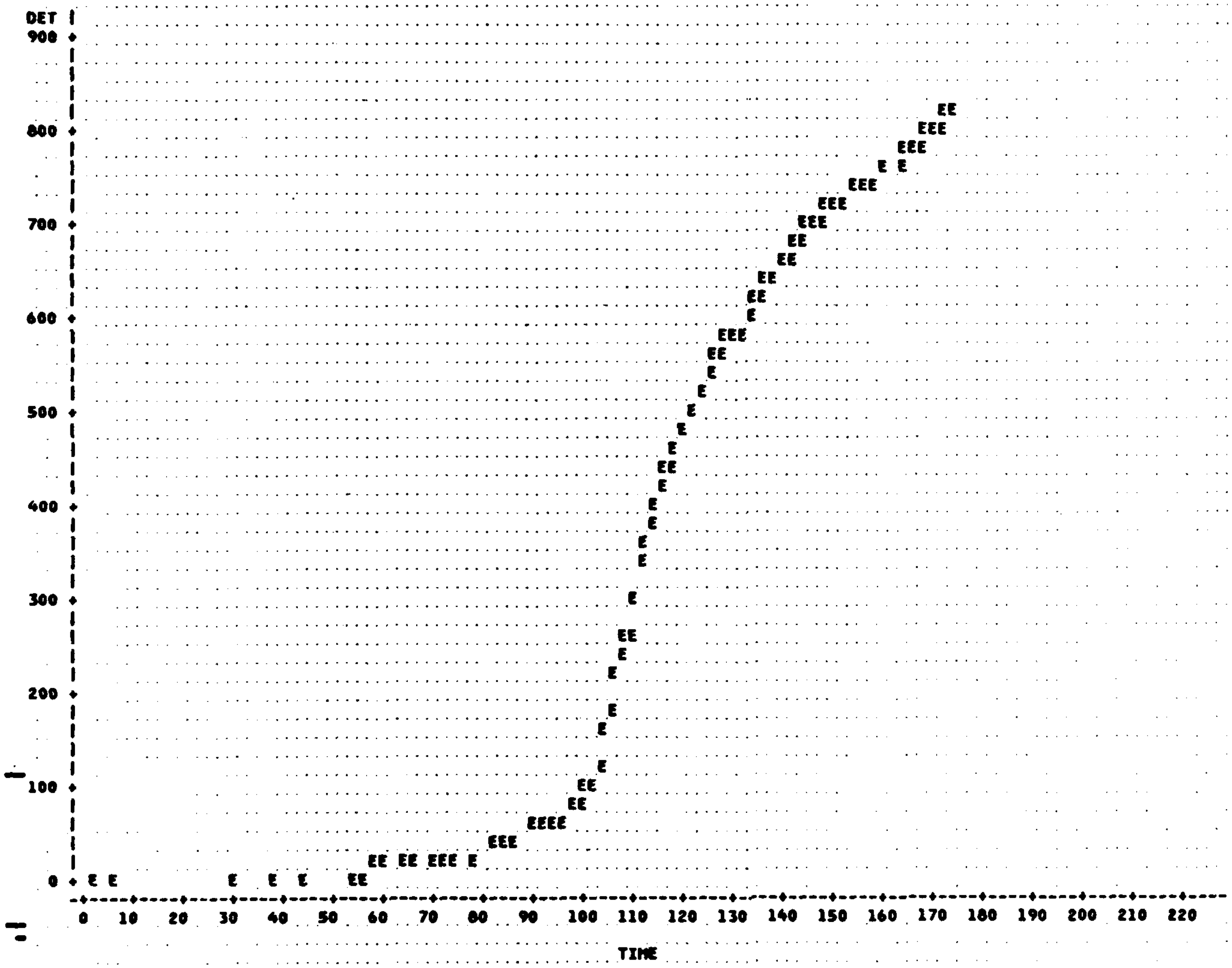


FIGURE 3.9.4
OSS

CUMULATIVE ERRORS DETECTED VS TIME

PLOT OF DET*TIME   SYMBOL USED IS E



NOTE: 27 OBS HIDDEN

FIGURE 3.9.5
SES

CUMULATIVE ERRORS DETECTED VS TIME

PLOT OF DET*TIME   SYMBOL USED IS E

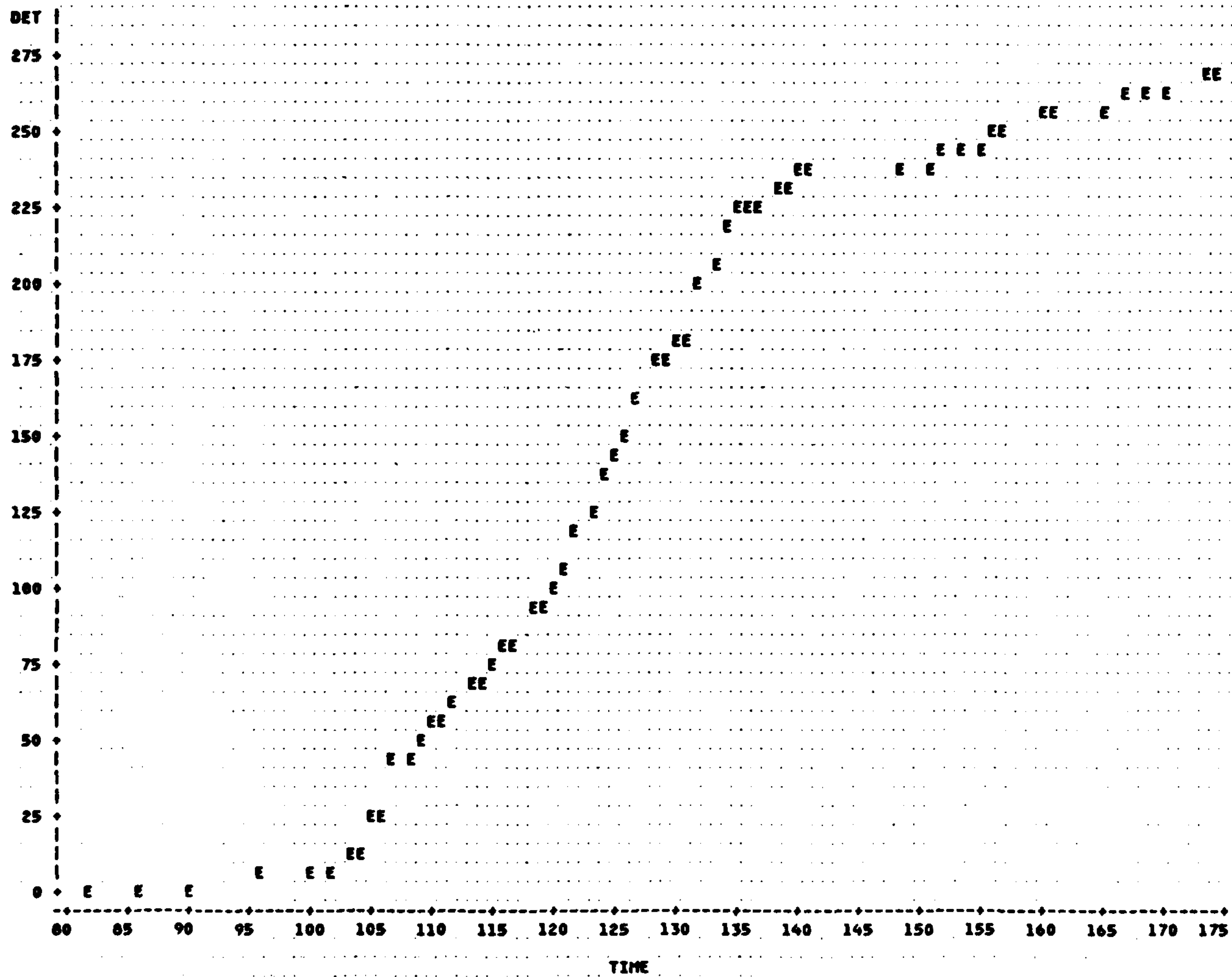
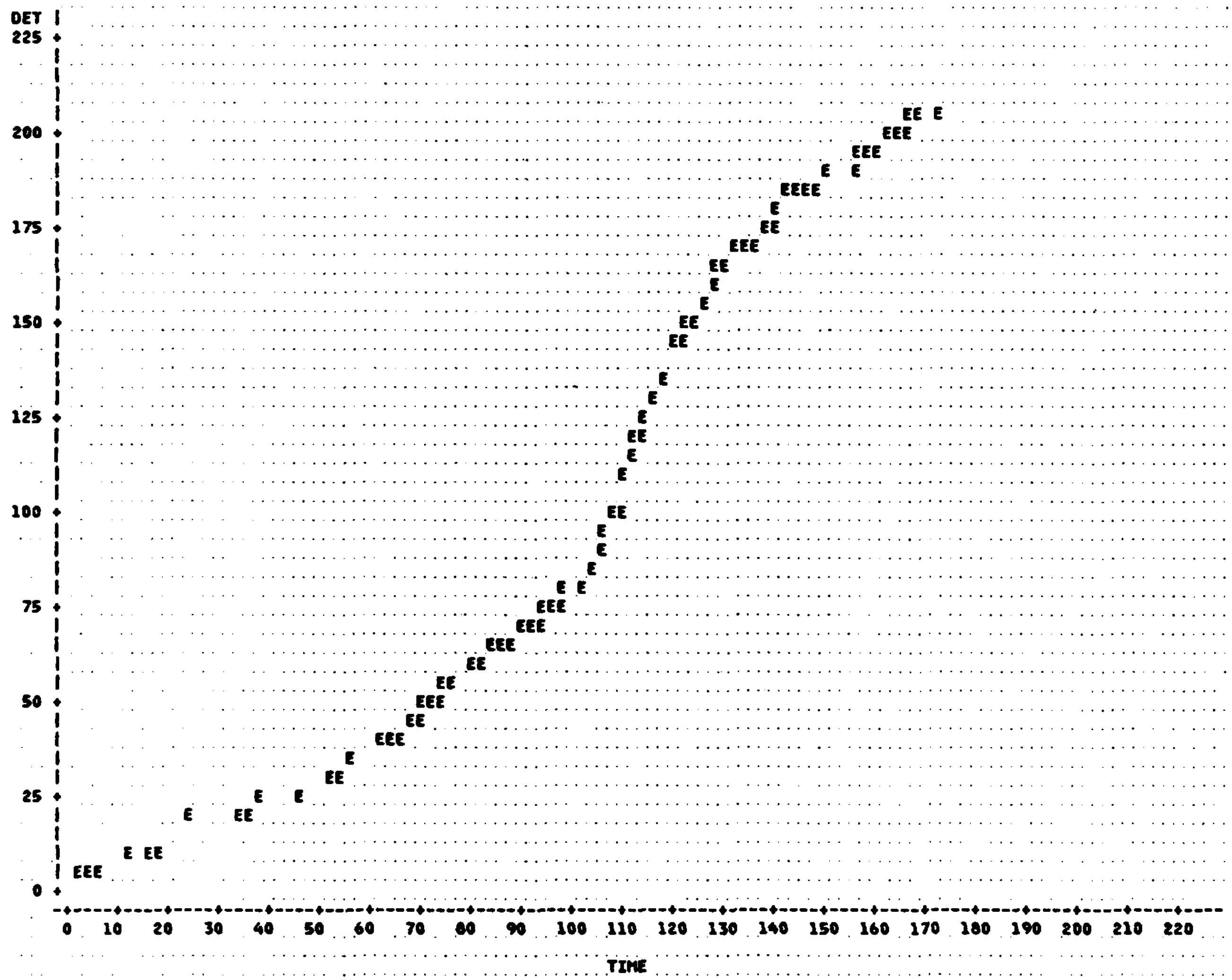


FIGURE 3.9.6
SUS

CUMULATIVE ERRORS DETECTED VS TIME

PLOT OF DET*TIME   SYMBOL USED IS E

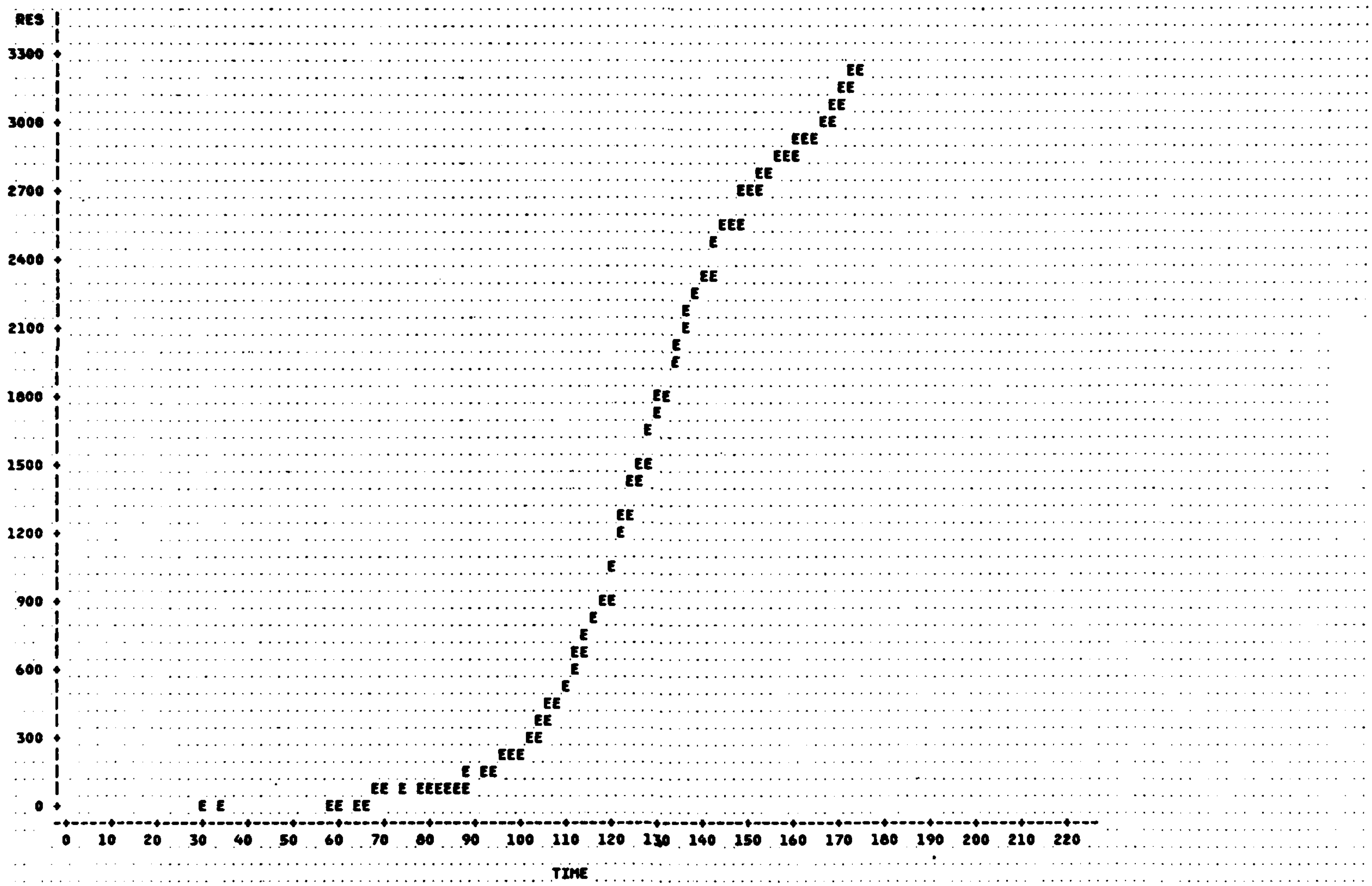


NOTE: 16 OBS HIDDEN

FIGURE 3.9.7
APS

CUMULATIVE ERRORS RESOLVED VS TIME

PLOT OF RES*TIME   SYMBOL USED IS E



NOTE: 27 OBS HIDDEN

FIGURE 3.9.8
DIS

CUMULATIVE ERRORS RESOLVED VS TIME

PLOT OF RES*TIME SYMBOL USED IS E

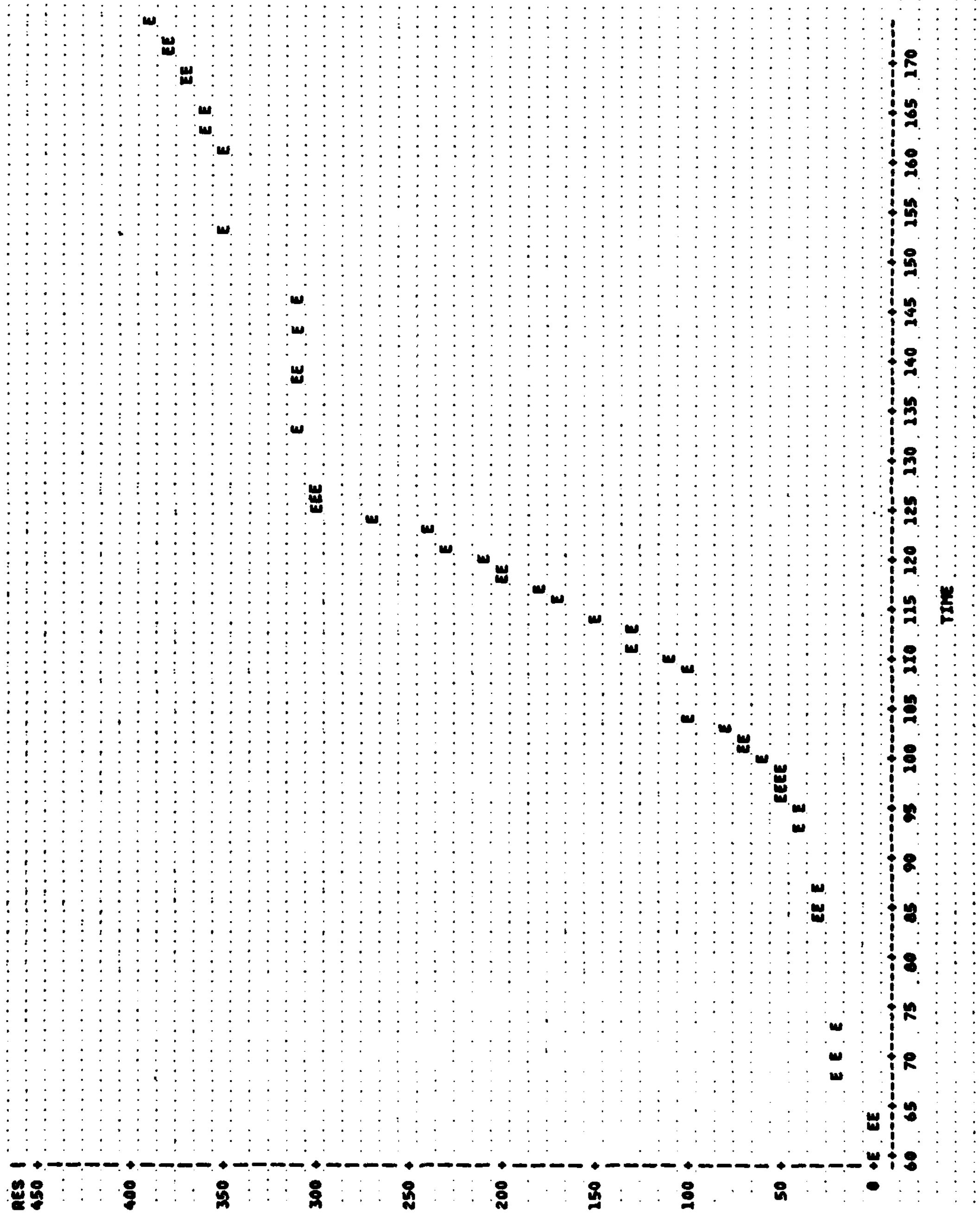


FIGURE 3.9.9
DRS

CUMULATIVE ERRORS RESOLVED VS TIME

PLOT OF RES*TIME   SYMBOL USED IS E

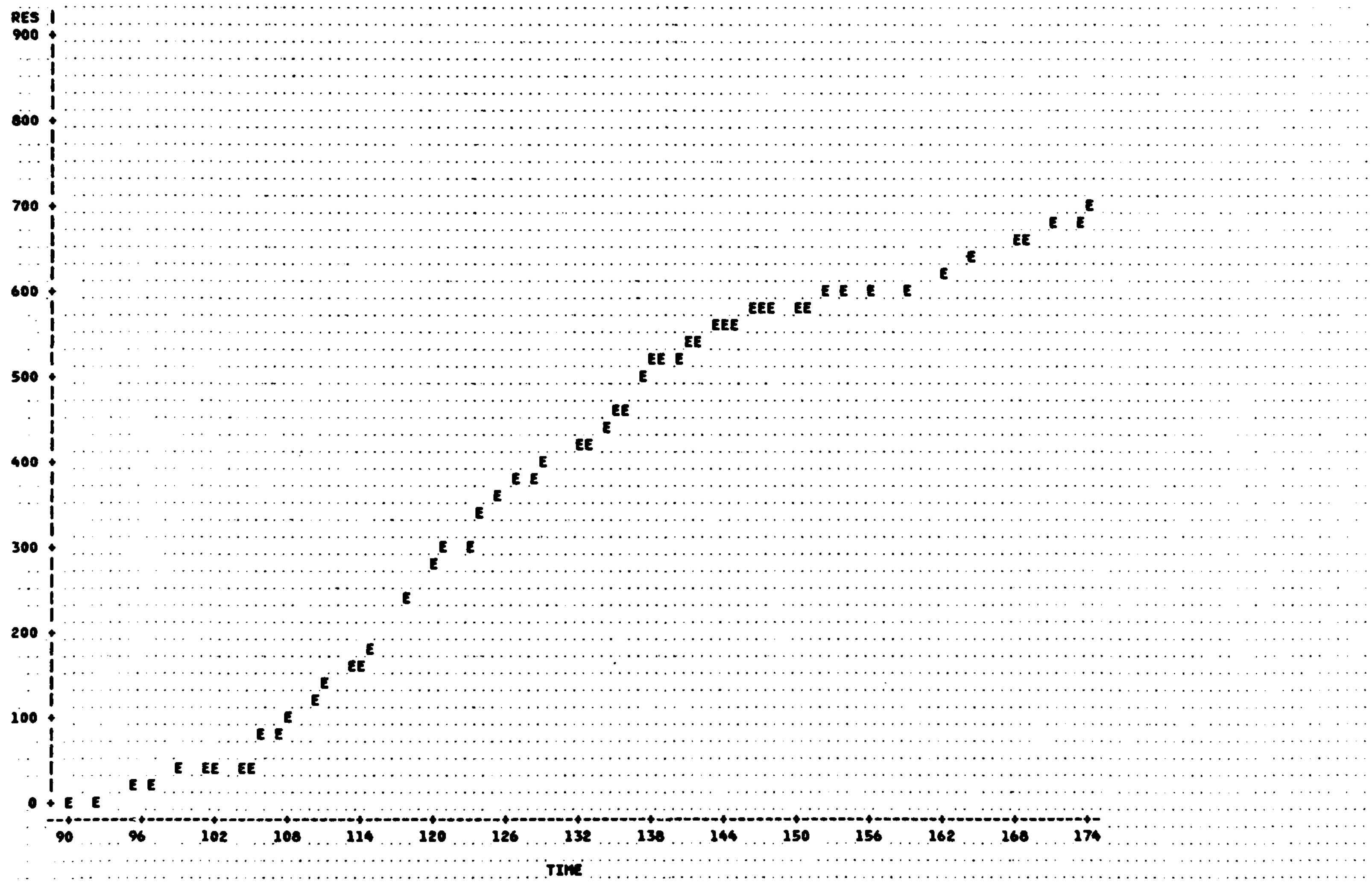
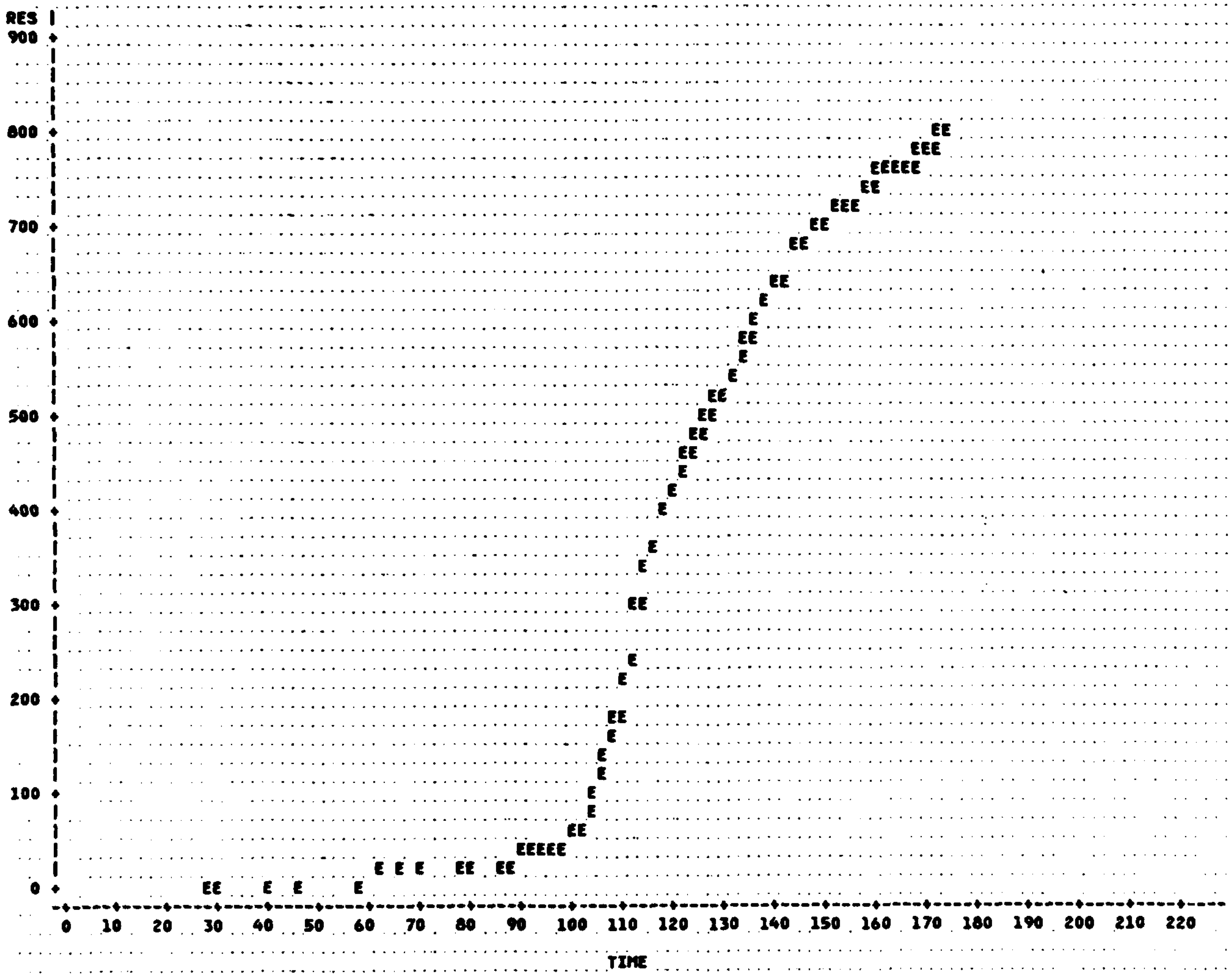


FIGURE 3.9.10
OSS

CUMULATIVE ERRORS RESOLVED VS TIME

PLOT OF RES*TIME SYMBOL USED IS E



NOTE: 18 OBS HIDDEN

FIGURE 3.9.11
SES

CUMULATIVE ERRORS RESOLVED VS TIME

PLOT OF RES*TIME SYMBOL USED IS E

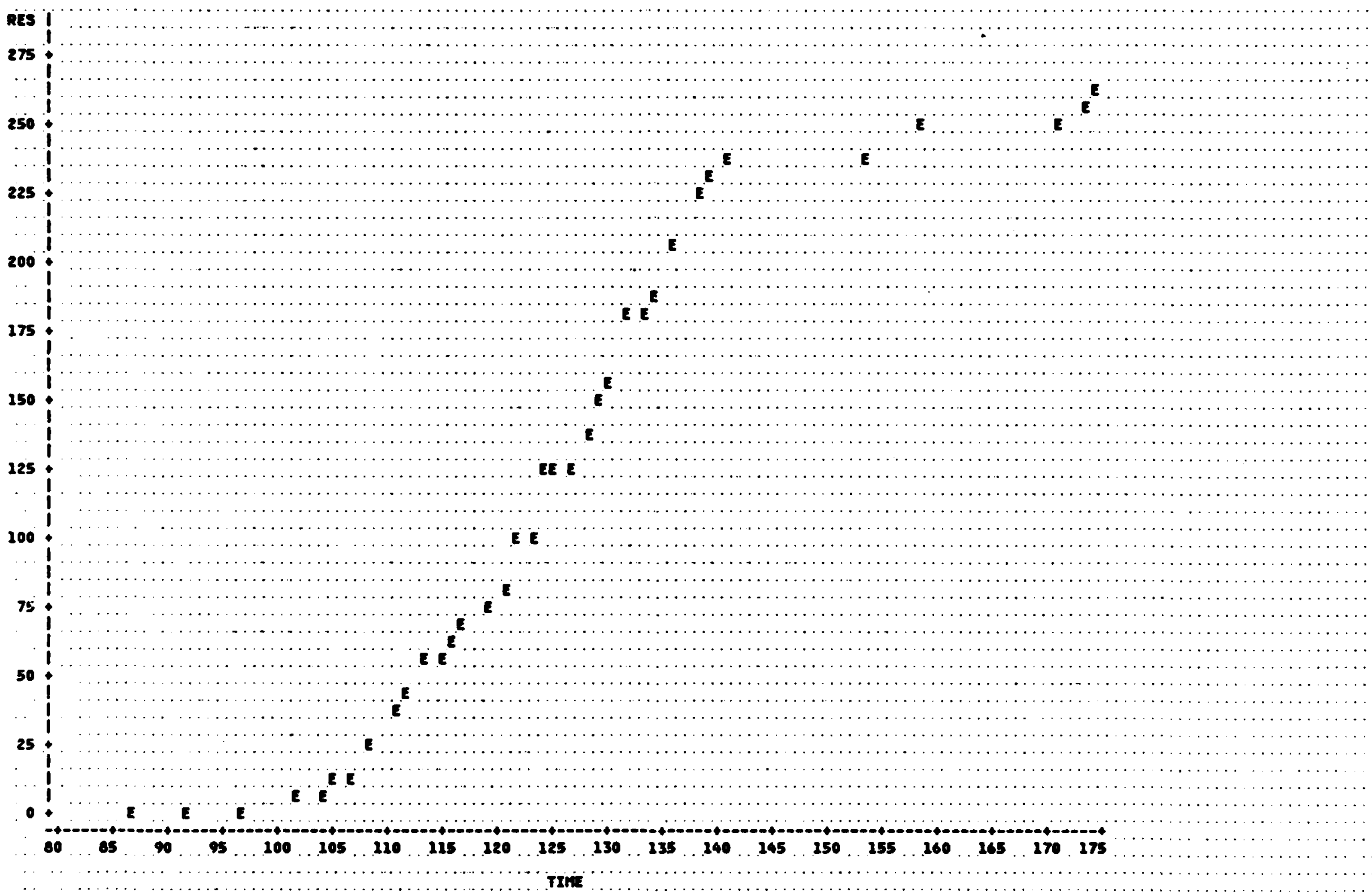
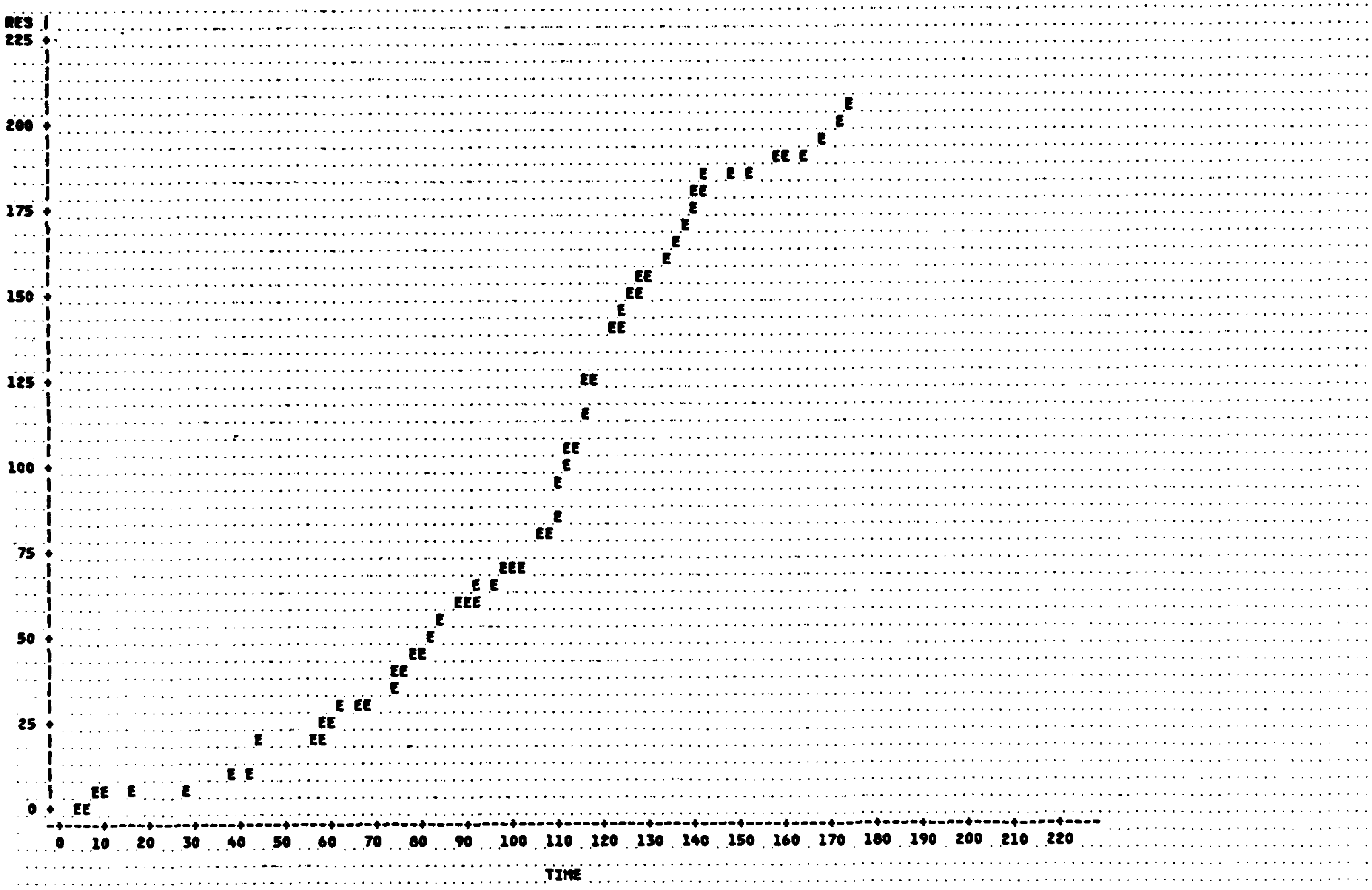


FIGURE 3.9.12
SUS

CUMULATIVE ERRORS RESOLVED VS TIME

PLOT OF RES*TIME SYMBOL USED IS E



NOTE: 4 OBS HIDDEN

by restricting attention to a single test phase the testing intensity and methodology remain fairly consistent.

The effects of varying manpower on JSS could not be controlled, although we suspect that the major effects were test phase and software build-up, with manpower variation playing a lesser role.

3.10 Parameter Estimation

In this investigation we have used the equations/methods of parameter estimation advocated by the respective software reliability model authors. These methods are described as follows.

Based on a set of observations $n_1, n_2, \ldots n_k$ of the number of errors observed in k successive, nonoverlapping time periods of lengths $\tau_1, \tau_2, \ldots \tau_k$, the natural logarithm of the models likelihood function evaluated at the observations is differentiated with respect to each parameter, and the resulting expressions set equal to zero and solved for the parameter values. This method of estimation has been referred to by the authors as "maximum likelihood", but this is not, strictly speaking, the maximum likelihood technique for the following reasons.

First, all but two of the models have the parameter N (the number of initial errors) which is known to be positive integer valued and at least as large as the number of errors removed from the software under investigation. Hence, differentiation with respect to N is not appropriate, and moreover, the solutions to the resulting equations do not yield integer values for N. Secondly, other parameters also have restrictions ($a > 0$, $b > 0$ in the Nonhomogeneous Poisson Model; $0 < K < 1$, $\lambda > 0$ in the Geometric Poisson Model; $\phi > 0$ in the Generalized Poisson Model, Binomial Model, IBM Poisson Model, and Imperfect Debugging Model). This estimation technique advocated by the authors does not guarantee that these restrictions will be met. Finally, setting the derivatives of the log of the likelihood function equal to zero and solving for the parameter values does not necessarily yield parameter values which indeed maximize the likelihood function (which is the principle of the maximum likelihood technique). For these reasons, we will refer to this method as "pseudo maximum likelihood estimation".

In the case of the Binomial model, a different technique is used. In that model the authors suggest that the parameters N and a be estimated by solving

$$\frac{\partial Q}{\partial N} = \frac{\partial Q}{\partial a} = 0$$

where

$$Q = \sum_{i=1}^{k} \{N_i - (1-e^{-a\tau_i})(N-\sum_{j=1}^{i-1} N_j)\}^2.$$

This technique must be termed "pseudo least squares" for the same or similar reasons cited above for the pseudo maximum likelihood case. That is, this technique does not necessarily result in minimizing Q, and it does not yield estimates for N and a which are integer valued and positive, respectively.

To our knowledge, it is not known under what conditions these estimators possess good statistical properties (i.e. consistency, efficiency, asymptotic normality, etc.). In a simulation study performed in Schafer et.al. (1979), it was observed that these techniques apparently do lead to consistent (i.e. stochastically convergent to the true parameter value) and asymptotically normal estimators for the Jelinski-Moranda, Generalized Poisson, Binomial, and Nonhomogeneous Poisson models. Moreover, the same simulation study showed that the variance of the pseudo maximum likelihood estimators was less (both asymptotically and as observed in the small sample simulations) than the corresponding psuedo least squares estimators for the Jelinski-Moranda and Nonhomogeneous Poisson Models.

While these results suggest that the pseudo maximum likelihood and pseudo least squares estimators advocated by the authors of the models do yield "good" estimates when the model assumptions are satisfied, it was also noted in Schafer et.al. (1979) that the lack of starting points for the Newton-Raphson procedure for solving the equations defining the estimators was a serious problem. That problem prevailed in this study also. Thus, often in the course of estimating the model parameters the iterative Newton-Raphson procedure did not converge, or it converged to parameter values which were not allowable (e.g. negative values for N). These difficulties are very damaging to the models in terms of their use by software acquisition managers.

3.11 A Software Reliability Measure Derivable from each of the Models

As required by the statement of work, it was necessary to derive measures from each software reliability model's outputs which would provide assistance to project office personnel in monitoring formal and qualification testing of software projects. By "model outputs" is meant the parameter estimates which result from fitting the model. These parameters and their physical interpretations, are described in Sections 3.2 through 3.7.

In surveying the various reliability measures proposed by the authors of the models, we found most of them to be inadequate because that they were time-unit dependent. Because only calendar time is collected in the JSS database, and because this time measure is not uniformly representative of test phase time nor system operational time, we do not recommend such measures as mean time to next error, mean time to achieve a certain number of remaining errors, probability distribution of the time to next error, etc. These measures can be very misleading to project

personnel when predicted based on models' fit to calendar-time data.

The measure we feel would be of most assistance to project personnel is the number of errors remaining. This measure has many advantages, the most important of which is the fact that the purpose of software testing is to identify (and, as a result, remove) software errors. Thus, residual errors is a direct measure of the effectiveness of the debugging process. Another advantage of this measure is that it can be directly computed from the outputs of each model, greatly facilitating comparison (actually, for the Nonhomogeneous Poisson and Geometric Poisson Models, the analogous measure is the expected number of residual errors). Another strong advantage is that this measure is time independent.

Table 3.11.1 lists the formulas for estimating residual errors for each model in terms of the model parameter estimates.

Table 3.11.1

Formulas for Residual Errors

Model	Residual Errors Estimate*
Modified Imperfect Debugging	$\hat{N} - M$
Nonhomogeneous Poisson**	$\hat{a} - M$
Geometric Poisson**	$\hat{\lambda}/(1-\hat{K}) - M$
IBM Poisson	$\hat{N} - M$
Generalized Poisson	$\hat{N} - M$
Binomial	$\hat{N} - M$

* M is the total number of errors removed, "hats" signify estimates.

** These are actually estimated expected residual errors

4. RESULTS OF SOFTWARE RELIABILITY MODEL FITTING

4.1 Data Compilation

The most important investigation of this effort was the actual application of the software reliability models to the JSS data to determine their degree of applicability. To accomplish this, it was first necessary to compile a number of datasets from the JSS database on which to apply the models. The rationale for choosing these datasets was established to insure that, as far as possible, none of the models' assumptions were violated because of the way in which the JSS data were compiled.

This rationale included the selection of data from four test phases only; IT (integration test), SD (independent test), ST (System Test), and IN (installation test). Each dataset was segregated by test phase to guard against the effects of testing intensity on the software error rate. Each dataset was also segregated by Compilation Unit (CU) to guard against the effects of software build-up (since all the software in a given CU enters the test phase at the same time), and to provide the maximum number of errors per dataset (the single module error rates are to small).

A listing of this data is given in Table 4.1.1. In this table, each dataset is identified by the CPCI, CU, and test phase (e.g. APS, APC, IT). The first column of numbers represents the successive numbers of errors detected in successive intervals of time. The second column gives the time interval lengths in calendar weeks. The third column is the total number of errors removed prior to the beginning of the corresponding time period. The fourth and fifth columns are cumulative total time and cumulative total errors detected. This data was extracted from the JSS database as it existed during week 182 of the implementation phase (IP). Subsequently, two compilation units (AAZ, MMC) were relocated from CPCI APS to CPCI OSS. Thus, the installation phase was not complete. All data is from IP.

The time intervals were chosen so that no errors were removed during the time intervals, but only at the beginning of the time periods. This was accomplished by choosing the time interval endpoints to be the times at which error removals clustered in the raw data. This selection of time intervals was choosen solely for the purpose of attempting to satisfy the model assumptions.

At the end of each dataset in Table 4.1.1, the total number of errors observed and removed are printed for the particular dataset. These numbers will generally be one more than the last number in the cumulative error count column and error removal column for the dataset. The reason for this is that it was not known exactly how much test time was accumulated when the

TABLE 4.1.1
DATA SETS FOR APPLICATION OF SOFTWARE RELIABILITY MODELS

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
APS	APC	IT					
			2	7	0	7	2
			4	21	1	28	6
			0	8	4	36	6
			0	2	5	38	6
			3	3	6	41	9
			2	4	8	45	11
			11	6	12	51	22
			3	1	13	52	25
			0	2	23	54	25
			1	1	24	55	26
			1	3	26	58	27
			1	2	27	60	28
			1	2	28	62	29
			0	3	29	65	29
			1	6	30	71	30
			1	23	31	94	31
			2	4	32	98	33
			1	9	34	107	34

TOTAL ERRORS DETECTED= 35 TOTAL REMOVED= 35
DATA BEGINS AT WEEK 64 OF IMPLEMENTATION PHASE

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
APS	APC	ST					
			4	3	0	3	4
			8	4	5	7	12
			1	1	7	8	13
			2	4	11	12	15
			0	4	15	16	15

TOTAL ERRORS DETECTED= 16 TOTAL REMOVED= 16
DATA BEGINS AT WEEK 151 OF IMPLEMENTATION PHASE

TABLE 4.1.1 (CONTINUED)
DATA SETS FOR APPLICATION OF SOFTWARE RELIABILITY MODELS

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
APS	APC	IN					
			2	1	0	1	2
			1	1	1	2	3
			9	6	4	8	12
			1	2	11	10	13
			4	2	12	12	17
			3	1	13	13	20
			0	2	20	15	20

TOTAL ERRORS DETECTED= 21 TOTAL REMOVED= 21
DATA BEGINS AT WEEK 163 OF IMPLEMENTATION PHASE

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
APS	ZEZ	IT					
			0	56	0	56	0
			1	18	1	74	1
			12	13	2	87	13
			3	2	3	89	16
			3	1	11	90	19
			1	3	19	93	20
			1	2	21	95	21
			1	4	22	99	22
			1	18	23	117	23

TOTAL ERRORS DETECTED= 24 TOTAL REMOVED= 24
DATA BEGINS AT WEEK 87 OF IMPLEMENTATION PHASE

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
APS	ZEZ	SD					
			0	3	0	3	0
			19	6	1	9	19
			1	1	3	10	20
			2	1	9	11	22
			5	2	10	13	27
			4	1	20	14	31
			20	3	21	17	51
			8	1	38	18	59
			1	1	39	19	60
			9	3	54	22	69
			0	2	67	24	69
			3	2	69	26	72
			1	2	72	28	73
			0	3	73	31	73

TOTAL ERRORS DETECTED= 74 TOTAL REMOVED= 74
DATA BEGINS AT WEEK 114 OF IMPLEMENTATION PHASE

TABLE 4.1.1 (CONTINUED)
DATA SETS FOR APPLICATION OF SOFTWARE RELIABILITY MODELS

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
APS	ZEZ	ST					
			0	1	0	1	0
			3	3	1	4	3
			5	2	2	6	8
			8	3	8	9	16
			1	1	14	10	17
			5	8	18	18	22
			2	4	22	22	24
			0	1	23	23	24
			1	4	24	27	25

TOTAL ERRORS DETECTED= 26 TOTAL REMOVED= 26
DATA BEGINS AT WEEK 134 OF IMPLEMENTATION PHASE

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
APS	ZEZ	IN					
			5	3	0	3	5
			0	2	2	5	5
			1	2	3	7	6
			3	5	6	12	9
			0	3	9	15	9

TOTAL ERRORS DETECTED= 10 TOTAL REMOVED= 10
DATA BEGINS AT WEEK 166 OF IMPLEMENTATION PHASE

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
APS	ASZ	IT					
			3	54	0	54	3
			0	2	1	56	3
			0	4	2	60	3
			2	5	3	65	5
			1	2	4	67	6
			0	1	5	68	6
			2	1	6	69	8
			2	1	7	70	10
			10	3	11	73	20
			3	1	15	74	23
			1	1	20	75	24
			12	5	23	80	36
			3	2	32	82	39
			1	1	35	83	40
			1	2	39	85	41
			2	2	40	87	43
			2	2	42	89	45
			0	2	43	91	45
			2	3	46	94	47
			3	3	48	97	50
			2	1	49	98	52
			1	1	51	99	53
			1	1	52	100	54
			2	6	55	106	56
			1	5	56	111	57

TOTAL ERRORS DETECTED= 58 TOTAL REMOVED= 58

DATA BEGINS AT WEEK 91 OF IMPLEMENTATION PHASE

TABLE 4.1.1 (CONTINUED)
DATA SETS FOR APPLICATION OF SOFTWARE RELIABILITY MODELS

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
APS	ASZ	SD					
			1	1	0	1	1
			3	3	1	4	4
			5	2	2	6	9
			0	1	5	7	9
			2	2	7	9	11
			2	4	11	13	13
			1	2	12	15	14
			2	3	13	18	16
			0	3	15	21	16
			2	5	17	26	18
			1	4	19	30	19

TOTAL ERRORS DETECTED= 20 TOTAL REMOVED= 20
DATA BEGINS AT WEEK 114 OF IMPLEMENTATION PHASE

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
APS	ASZ	ST					
			0	1	0	1	0
			3	7	1	8	3
			3	5	3	13	6
			3	3	7	16	9
			1	4	10	20	10

TOTAL ERRORS DETECTED= 11 TOTAL REMOVED= 11
DATA BEGINS AT WEEK 136 OF IMPLEMENTATION PHASE

AD-A138 196 RELIABILITY MODEL DEMONSTRATION STUDY VOLUME 1(U) 2/4
HUGHES AIRCRAFT CO FULLERTON CA GROUND SYSTEMS GROUP
J E ANGUS ET AL. AUG 83 RADC-TR-83-207-VOL-1
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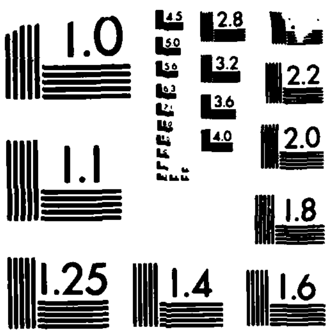


MICROCOPY RESOLUTION TEST CHART
NATIONAL BUREAU OF STANDARDS-1963-A

TABLE 4.1.1 (CONTINUED)
DATA SETS FOR APPLICATION OF SOFTWARE RELIABILITY MODELS

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
APS	ACZ	IT					
			0	1	0	1	0
			3	17	1	18	3
			5	3	3	21	8
			2	3	4	24	10
			0	1	5	25	10
			2	3	8	28	12
			2	2	12	30	14
			0	2	13	32	14
			3	6	14	38	17
			2	3	17	41	19
			0	1	18	42	19
			4	6	19	48	23
			1	5	20	53	24
			0	4	22	57	24
			0	6	23	63	24
			0	18	24	81	24

TOTAL ERRORS DETECTED= 25 TOTAL REMOVED= 25
DATA BEGINS AT WEEK 68 OF IMPLEMENTATION PHASE

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
APS	ACZ	ST					
			0	1	0	1	0
			1	7	1	8	1
			2	6	2	14	3
			2	3	3	17	5
			2	4	6	21	7
			1	5	7	26	8

TOTAL ERRORS DETECTED= 9 TOTAL REMOVED= 9
DATA BEGINS AT WEEK 135 OF IMPLEMENTATION PHASE

TABLE 4.1.1 (CONTINUED)
DATA SETS FOR APPLICATION OF SOFTWARE RELIABILITY MODELS

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
APS	MMC	IT					
			1	8	0	8	1
			0	11	1	19	1
			2	8	2	27	3
			1	7	4	34	4
			1	1	5	35	5
			2	5	6	40	7
			2	34	8	74	9
			2	4	9	78	11
			1	5	12	83	12
			1	6	13	89	13

TOTAL ERRORS DETECTED= 14 TOTAL REMOVED= 14
DATA BEGINS AT WEEK 85 OF IMPLEMENTATION PHASE

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
APS	MMC	SD					
			1	1	0	1	1
			0	4	1	5	1
			2	5	2	10	3
			1	6	3	16	4
			0	2	4	18	4

TOTAL ERRORS DETECTED= 5 TOTAL REMOVED= 5
DATA BEGINS AT WEEK 151 OF IMPLEMENTATION PHASE

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
APS	MMC	ST					
			2	3	0	3	2
			6	4	1	7	8
			3	5	7	12	11
			2	6	11	18	13

TOTAL ERRORS DETECTED= 14 TOTAL REMOVED= 14
DATA BEGINS AT WEEK 151 OF IMPLEMENTATION PHASE

TABLE 4.1.1 (CONTINUED)
DATA SETS FOR APPLICATION OF SOFTWARE RELIABILITY MODELS

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
APS	MMC	IN					
			8	5	0	5	8
			2	1	1	6	10
			9	4	5	10	19
			6	4	16	14	25
			1	1	24	15	26

TOTAL ERRORS DETECTED= 27 TOTAL REMOVED= 27
DATA BEGINS AT WEEK 165 OF IMPLEMENTATION PHASE

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
APS	ATZ	IT					
			4	28	0	28	4
			3	14	5	42	7
			0	1	7	43	7
			2	4	8	47	9
			0	2	9	49	9
			1	5	10	54	10
			2	3	11	57	12
			1	1	13	58	13
			1	2	14	60	14
			1	18	15	78	15

TOTAL ERRORS DETECTED= 16 TOTAL REMOVED= 16
DATA BEGINS AT WEEK 105 OF IMPLEMENTATION PHASE

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
APS	ATZ	SD					
			1	6	0	6	1
			2	3	1	9	3
			2	2	2	11	5
			4	2	3	13	9
			3	4	8	17	12

TOTAL ERRORS DETECTED= 13 TOTAL REMOVED= 13
DATA BEGINS AT WEEK 117 OF IMPLEMENTATION PHASE

TABLE 4.1.1 (CONTINUED)
DATA SETS FOR APPLICATION OF SOFTWARE RELIABILITY MODELS

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
APS	ATZ	ST					
			[illegible]	1	0	1	1
			[illegible]	3	1	4	3
			0	1	2	5	3
			2	8	4	13	5
			1	15	6	28	6

TOTAL ERRORS DETECTED= 7 TOTAL REMOVED= 7
DATA BEGINS AT WEEK 139 OF IMPLEMENTATION PHASE

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
APS	AAZ	IT					
			1	3	0	3	1
			3	3	1	6	4
			1	3	4	9	5
			2	8	6	17	7
			4	5	8	22	11
			0	1	9	23	11
			3	9	12	32	14
			1	3	14	35	15
			2	7	16	42	17
			1	2	17	44	18
			1	29	19	73	19

TOTAL ERRORS DETECTED= 20 TOTAL REMOVED= 20
DATA BEGINS AT WEEK 85 OF IMPLEMENTATION PHASE

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
APS	AAZ	SD					
			1	6	0	6	1
			0	2	1	8	1
			3	7	2	15	4
			2	2	3	17	6
			2	3	6	20	8
			0	8	8	28	8
			1	16	9	44	9

TOTAL ERRORS DETECTED= 10 TOTAL REMOVED= 10
DATA BEGINS AT WEEK 117 OF IMPLEMENTATION PHASE

TABLE 4.1.1 (CONTINUED)
DATA SETS FOR APPLICATION OF SOFTWARE RELIABILITY MODELS

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
APS	AAZ	ST					
			1	1	0	1	1
			1	2	1	3	2
			1	4	2	7	3
			1	8	3	15	4
			0	4	4	19	4
			3	5	5	24	7
			0	6	6	30	7
			0	10	7	40	7

TOTAL ERRORS DETECTED= 8 TOTAL REMOVED= 8
DATA BEGINS AT WEEK 137 OF IMPLEMENTATION PHASE

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
APS	AAZ	IN					
			3	3	0	3	3
			2	4	1	7	5
			0	2	4	9	5
			0	3	5	12	5

TOTAL ERRORS DETECTED= 6 TOTAL REMOVED= 6
DATA BEGINS AT WEEK 166 OF IMPLEMENTATION PHASE

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
APS	MEZ	IT					
			1	14	0	14	1
			8	9	1	23	9
			6	2	5	25	15
			2	2	6	27	17
			4	1	15	28	21
			0	2	16	30	21
			1	5	21	35	22
			0	1	22	36	22
			1	7	23	43	23
			1	5	24	48	24
			1	2	25	50	25
			1	2	26	52	26
			2	11	27	63	28
			1	22	29	85	29

TOTAL ERRORS DETECTED= 30 TOTAL REMOVED= 30
DATA BEGINS AT WEEK 99 OF IMPLEMENTATION PHASE

TABLE 4.1.1 (CONTINUED)
DATA SETS FOR APPLICATION OF SOFTWARE RELIABILITY MODELS

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
APS	MEZ	SD					
			4	1	0	1	4
			1	4	3	5	5
			1	2	6	7	6
			1	6	7	13	7
			1	3	8	16	8
			1	21	9	37	9

TOTAL ERRORS DETECTED= 10 TOTAL REMOVED= 10
DATA BEGINS AT WEEK 124 OF IMPLEMENTATION PHASE

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
APS	MEZ	ST					
			1	1	0	1	1
			3	3	2	4	4
			0	1	3	5	4
			2	5	5	10	6
			1	12	7	22	7

TOTAL ERRORS DETECTED= 8 TOTAL REMOVED= 8
DATA BEGINS AT WEEK 139 OF IMPLEMENTATION PHASE

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
APS	HTZ	IT					
			1	5	0	5	1
			1	7	1	12	2
			2	5	2	17	4
			2	1	4	18	6
			2	3	7	21	8
			0	1	8	22	8
			2	6	9	28	10
			1	5	11	33	11

TOTAL ERRORS DETECTED= 12 TOTAL REMOVED= 12
DATA BEGINS AT WEEK 92 OF IMPLEMENTATION PHASE

TABLE 4.1.1 (CONTINUED)
DATA SETS FOR APPLICATION OF SOFTWARE RELIABILITY MODELS

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
APS	HTZ	SD					
			7	7	0	7	7
			7	1	6	8	14
			4	3	12	11	18
			1	4	16	15	19
			1	6	19	21	20
			0	1	20	22	20

TOTAL ERRORS DETECTED= 21 TOTAL REMOVED= 21
DATA BEGINS AT WEEK 120 OF IMPLEMENTATION PHASE

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
APS	HTZ	ST					
			1	1	0	1	1
			1	1	1	2	2
			2	2	3	4	4
			1	2	5	6	5
			2	3	6	9	7
			5	6	7	15	12
			2	7	13	22	14
			1	10	15	32	15

TOTAL ERRORS DETECTED= 16 TOTAL REMOVED= 16
DATA BEGINS AT WEEK 134 OF IMPLEMENTATION PHASE

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
APS	MIZ	IT					
			2	10	0	10	2
			0	2	2	12	2
			5	8	3	20	7
			0	1	6	21	7
			4	3	8	24	11
			3	2	11	26	14
			2	3	13	29	16
			0	4	16	33	16
			1	2	17	35	17

TOTAL ERRORS DETECTED= 18 TOTAL REMOVED= 18
DATA BEGINS AT WEEK 101 OF IMPLEMENTATION PHASE

TABLE 4.1.1 (CONTINUED)
DATA SETS FOR APPLICATION OF SOFTWARE RELIABILITY MODELS

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
APS	MIZ	SD					
			6	5	0	5	6
			6	4	7	9	12
			0	1	10	10	12
			3	4	13	14	15
			1	2	14	16	16
			0	2	15	18	16
			7	5	17	23	23
			0	1	19	24	23
			1	1	22	25	24
			0	2	24	27	24
			2	5	25	32	26
			1	23	27	55	27

TOTAL ERRORS DETECTED= 28 TOTAL REMOVED= 28
DATA BEGINS AT WEEK 115 OF IMPLEMENTATION PHASE

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
APS	MIZ	ST					
			4	1	0	1	4
			1	1	3	2	5
			2	1	5	3	7
			2	2	8	5	9
			2	3	10	8	11
			1	1	11	9	12
			1	1	12	10	13
			0	4	13	14	13
			2	12	14	26	15

TOTAL ERRORS DETECTED= 16 TOTAL REMOVED= 16
DATA BEGINS AT WEEK 135 OF IMPLEMENTATION PHASE

TABLE 4.1.1 (CONTINUED)
DATA SETS FOR APPLICATION OF SOFTWARE RELIABILITY MODELS

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
APS	DAZ	IT					
			3	2	0	2	3
			0	1	1	3	3
			14	6	4	9	17
			0	1	9	10	17
			7	3	15	13	24
			18	5	19	18	42
			2	1	34	19	44
			0	1	43	20	44
			5	2	44	22	49
			3	4	48	26	52
			3	5	53	31	55
			0	1	54	32	55
			0	1	55	33	55
			3	13	56	46	58
			0	3	58	49	58
			1	4	59	53	59
			0	1	60	54	59

TOTAL ERRORS DETECTED= 60 TOTAL REMOVED= 61
DATA BEGINS AT WEEK 104 OF IMPLEMENTATION PHASE

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
APS	DAZ	SD					
			3	2	0	2	3
			9	7	1	9	12
			3	2	9	11	15
			4	2	10	13	19
			4	4	14	17	23
			2	5	18	22	25
			0	1	21	23	25
			2	1	22	24	27
			0	1	24	25	27
			2	6	28	31	29
			1	18	30	49	30

TOTAL ERRORS DETECTED= 31 TOTAL REMOVED= 31
DATA BEGINS AT WEEK 113 OF IMPLEMENTATION PHASE

TABLE 4.1.1 (CONTINUED)
DATA SETS FOR APPLICATION OF SOFTWARE RELIABILITY MODELS

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
APS	DAZ	ST					
			5	2	0	2	5
			0	1	3	3	5
			3	2	5	5	8
			3	3	7	8	11
			0	1	10	9	11
			6	3	11	12	17
			2	2	14	14	19
			1	2	18	16	20
			2	1	19	17	22
			3	4	21	21	25
			0	1	23	22	25
			1	4	24	26	26
			0	4	26	30	26

TOTAL ERRORS DETECTED= 27 TOTAL REMOVED= 27
DATA BEGINS AT WEEK 136 OF IMPLEMENTATION PHASE

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
APS	DAZ	IN					
			2	2	0	2	2
			0	2	1	4	2
			1	2	3	6	3
			2	2	4	8	5
			3	4	5	12	8
			0	1	6	13	8
			0	2	8	15	8

TOTAL ERRORS DETECTED= 9 TOTAL REMOVED= 9
DATA BEGINS AT WEEK 164 OF IMPLEMENTATION PHASE

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
APS	SAD	IT					
			6	1	0	1	6
			8	1	2	2	14
			1	1	13	3	15
			4	3	15	6	19
			4	7	20	13	23
			6	5	23	18	29
			3	2	28	20	32
			2	2	32	22	34
			7	2	33	24	41
			4	3	38	27	45
			2	2	43	29	47
			0	1	44	30	47
			1	1	48	31	48
			1	20	49	51	49
			1	5	50	56	50

TOTAL ERRORS DETECTED= 51 TOTAL REMOVED= 51
DATA BEGINS AT WEEK 105 OF IMPLEMENTATION PHASE

TABLE 4.1.1 (CONTINUED)
DATA SETS FOR APPLICATION OF SOFTWARE RELIABILITY MODELS

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
APS	SAD	SD					
			3	1	0	1	3
			6	2	1	3	9
			0	1	2	4	9
			6	1	5	5	15
			2	1	6	6	17
			2	1	8	7	19
			16	4	15	11	35
			6	2	28	13	41
			4	2	31	15	45
			1	3	38	18	46
			1	3	41	21	47
			0	1	45	22	47
			1	1	47	23	48
			1	1	48	24	49
			1	6	50	30	50
			1	8	51	38	51

TOTAL ERRORS DETECTED= 52 TOTAL REMOVED= 52
DATA BEGINS AT WEEK 114 OF IMPLEMENTATION PHASE

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
APS	SAD	ST					
			0	1	0	1	0
			3	1	1	2	3
			0	1	3	3	3
			7	3	4	6	10
			2	4	10	10	12
			3	5	13	15	15
			4	3	16	18	19
			0	2	17	20	19
			0	2	18	22	19

TOTAL ERRORS DETECTED= 20 TOTAL REMOVED= 20
DATA BEGINS AT WEEK 134 OF IMPLEMENTATION PHASE

TABLE 4.1.1 (CONTINUED)
DATA SETS FOR APPLICATION OF SOFTWARE RELIABILITY MODELS

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
APS	ZBZ	IT					
			0	1	0	1	0
			2	5	1	6	2
			13	10	2	16	15
			2	1	9	17	17
			1	3	15	20	18
			0	1	16	21	18
			0	3	18	24	18
			1	6	19	30	19
			1	14	20	44	20

TOTAL ERRORS DETECTED= 21 TOTAL REMOVED= 21
DATA BEGINS AT WEEK 105 OF IMPLEMENTATION PHASE

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
APS	ZBZ	SD					
			1	3	0	3	1
			26	6	2	9	27
			4	1	4	10	31
			6	1	16	11	37
			10	2	18	13	47
			13	4	36	17	60
			4	2	57	19	64
			4	1	62	20	68
			4	2	63	22	72
			0	1	71	23	72
			2	1	72	24	74
			1	1	73	25	75
			1	1	75	26	76
			1	5	77	31	77
			2	6	78	37	79
			0	3	79	40	79

TOTAL ERRORS DETECTED= 80 TOTAL REMOVED= 80
DATA BEGINS AT WEEK 114 OF IMPLEMENTATION PHASE

TABLE 4.1.1 (CONTINUED)
DATA SETS FOR APPLICATION OF SOFTWARE RELIABILITY MODELS

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
APS	ZBZ	ST					
			3	1	0	1	3
			1	1	3	2	4
			2	1	4	3	6
			2	1	5	4	8
			5	2	7	6	13
			11	3	12	9	24
			2	1	23	10	26
			5	1	26	11	31
			0	4	27	15	31
			4	3	32	18	35
			6	4	35	22	41
			0	5	41	27	41

TOTAL ERRORS DETECTED= 42 TOTAL REMOVED= 42
DATA BEGINS AT WEEK 134 OF IMPLEMENTATION PHASE

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
DRS	DAD	IT					
			1	4	0	4	1
			1	7	2	11	2
			1	4	3	15	3
			11	7	4	22	14
			0	2	5	24	14
			1	3	6	27	15
			1	10	15	37	16
			0	8	16	45	16
			1	9	17	54	17
			2	11	18	65	19
			0	6	19	71	19

TOTAL ERRORS DETECTED= 20 TOTAL REMOVED= 20
DATA BEGINS AT WEEK 95 OF IMPLEMENTATION PHASE

TABLE 4.1.1 (CONTINUED)
DATA SETS FOR APPLICATION OF SOFTWARE RELIABILITY MODELS

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
OSS	LDR	SD					
			10	2	0	2	10
			1	1	1	3	11
			1	1	2	4	12
			10	6	12	10	22
			1	2	17	12	23
			1	7	20	19	24
			0	3	21	22	24
			1	4	22	26	25
			2	5	23	31	27
			0	2	24	33	27
			0	1	27	34	27

TOTAL ERRORS DETECTED= 28 TOTAL REMOVED= 28
DATA BEGINS AT WEEK 105 OF IMPLEMENTATION PHASE

TABLE 4.1.1 (CONTINUED)
DATA SETS FOR APPLICATION OF SOFTWARE RELIABILITY MODELS

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
OSS	LDR	ST					
			2	5	0	5	2
			1	4	1	9	3
			1	5	3	14	4
			1	3	4	17	5
			1	2	5	19	6
			0	1	6	20	6
			4	8	7	28	10
			0	2	10	30	10

TOTAL ERRORS DETECTED= 11 TOTAL REMOVED= 11
DATA BEGINS AT WEEK 125 OF IMPLEMENTATION PHASE

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
SES	VAS	IT					
			3	7	0	7	3
			0	1	2	8	3
			3	7	3	15	6
			2	2	4	17	8
			0	1	5	18	8
			1	1	7	19	9
			0	1	8	20	9
			4	4	9	24	13
			0	4	11	28	13
			0	6	13	34	13

TOTAL ERRORS DETECTED= 14 TOTAL REMOVED= 14
DATA BEGINS AT WEEK 111 OF IMPLEMENTATION PHASE

TABLE 4.1.1 (CONTINUED)
DATA SETS FOR APPLICATION OF SOFTWARE RELIABILITY MODELS

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
SES	VAS	SD					
			0	2	0	2	0
			4	6	1	8	4
			0	1	2	9	4
			1	1	3	10	5
			0	6	4	16	5
			5	3	6	19	10
			1	2	9	21	11
			1	4	12	25	12
			6	4	13	29	18
			1	4	18	33	19
			0	2	19	35	19

TOTAL ERRORS DETECTED= 20 TOTAL REMOVED= 20
DATA BEGINS AT WEEK 105 OF IMPLEMENTATION PHASE

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
SES	VAS	ST					
			2	3	0	3	2
			1	1	1	4	3
			1	2	3	6	4
			0	8	4	14	4

TOTAL ERRORS DETECTED= 5 TOTAL REMOVED= 5
DATA BEGINS AT WEEK 138 OF IMPLEMENTATION PHASE

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
SUS	CON	IT					
			1	1	0	1	1
			1	3	1	4	2
			0	4	2	8	2
			3	63	3	71	5
			3	8	5	79	8
			0	6	6	85	8
			1	12	7	97	9
			5	7	9	104	14
			1	3	12	107	15
			1	1	13	108	16
			6	2	15	110	22
			6	3	18	113	28
			1	1	25	114	29
			0	1	28	115	29
			0	4	29	119	29

TOTAL ERRORS DETECTED= 30 TOTAL REMOVED= 30
DATA BEGINS AT WEEK 3 OF IMPLEMENTATION PHASE

TABLE 4.1.1 (CONTINUED)
DATA SETS FOR APPLICATION OF SOFTWARE RELIABILITY MODELS

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
SUS	CON	SD					
			3	12	0	12	3
			4	5	1	17	7
			0	1	2	18	7
			3	5	7	23	10
			0	2	10	25	10

TOTAL ERRORS DETECTED= 11 TOTAL REMOVED= 11
DATA BEGINS AT WEEK 110 OF IMPLEMENTATION PHASE

CPCI	CU	PHASE	ERRORS DETECTED	TIME INTERVAL	CUM. ERRORS REMOVED	CUM. TIME	CUM. ERRORS DETECTED
SUS	CON	ST					
			0	4	0	4	0
			5	5	1	9	5
			0	5	3	14	5
			1	3	4	17	6
			0	2	5	19	6
			2	1	7	20	8
			1	1	8	21	9
			0	1	9	22	9
			2	16	10	38	11
			0	10	11	48	11

TOTAL ERRORS DETECTED= 12 TOTAL REMOVED= 12
DATA BEGINS AT WEEK 124 OF IMPLEMENTATION PHASE

first error was detected. The time at which the first error was detected was therefore selected as the time origin and the first error not counted in the data. Loss of this information should not critically affect the fit of the models overall.

4.2 Model Fitting

Each software reliabiliy model was applied to each dataset listed in Table 4.1.1 of Section 4.1 and estimates of the associated parameters attempted. In each attempt, if convergence of the iterative procedures was not obtained after several attempts with different starting points, or if convergence to invalid parameter estimates was obtained, the attempt was judged unsuccessful. The models were fit in the following order: Geometric Poisson, Jelinski-Moranda, Nonhomogeneous Poisson, Generalized Poisson, IBM Poisson (modified), Binomial, and IBM Poisson. For the Geometric Poisson, a starting value for K of 0.5 was used, since $0<K<1$. If convergence was obtained, then Table 3.8.1 was used to translate the Geometric Poisson parameters to parameter values for the other models. These values were then used as starting values for the other models. If convergence was not obtained for a starting value of $K=0.5$ for the Geometric Poisson model, then other starting points from (0,1) were tried; e.g. 0.125, 0.25, 0.625, 0.75, 0.875, etc. In general, if convergence was not obtained for a given model, several sets of starting points were tried. For example, if iteration was performed on N, then several starting values for N (all greater than the total number of errors removed for the dataset) were tried. Similarly, for iteration on ϕ (or b in the Nonhomogeneous Poisson Model) several starting points ranging from 0.001 up to 1.5 were tried. In general, if convergence was obtained and valid parameter estimates obtained for a given model, no effort was made to try other starting points in order to obtain convergence to different values. Such an investigation, although beyond the scope of this study, should be carried out in the future since the uniqueness of parameter estimates has not been addressed by the respective authors of the models.

Whenever the iterative procedures converged to valid parameter values, it was necessary to perform a statistical test of fit for the models.

Very little analysis has been performed by the authors of the models in connection with testing their fit.

Goel (1980) proposed a Kolmogorov-Smirnov test for testing the fit of the Nonhomogeneous Poisson Model when the times between software errors are available. However, on JSS, the exact times were not available, and moreover, the procedure advocated by Goel (1980) is not the correct use of the Kolmogorov-Smirnov test since the unknown parameters are estimated from the sample. Although this was recognized by Goel (1980), his suggested approach of doubling the significance level when choosing the

critical value has not been shown to be a valid approach for the model in question. A better approach would have been to Monte Carlo the sampling distribution of the Kolmogorov-Smirnov Statistic with the parameters estimated in order to obtain approximate true critical values. This was the approach in Schafer et.al. (1979) in determining the applicability of the classical Chi-square goodness-of-fit test when software reliability model parameters are estimated from the data. Since the data on JSS are available in grouped form only, this procedure is appropriate for analyzing the fit of the models to the JSS data.

Schafer et.al. (1979) observed that the classical chi-square goodness-of-fit test provided an adequate goodness-of-fit test for the Jelinski-Moranda, Generalized Poisson, Binomial, and Nonhomogeneous Poisson Models when their respective parameters are estimated from the sample. In view of the equivalence established between the Nonhomogeneous Poisson Model and the Geometric Poisson Model, this goodness-of-fit test should also be valid for the Geometric Poisson model. The test procedure is simple; based on N_i errors detected in time interval i of length $(1 \leq i \leq k)$ estimate the parameters of the software reliability model in question and form the statistic

$$\chi^2 = \sum_{i=1}^{k} \frac{(N_i - \hat{E}_i)^2}{\hat{E}_i}$$

where E_i is the expected value of N_i with the parameters relaced by their estimates. Obviously, large values of X^2 indicate deviation from the underlying model. In Schafer et.al. (1979) it was shown that under the assumption that the model is actually correct, the distribution of X^2 is approximately chi-square with k-1-e degrees of freedom where e is the number of parameters estimated. Thus, the goodness-of-fit test is to reject the validity of the model if the observed value of X^2 exceeds the $1-\gamma$ quantile of the chi-square distribution with k-1-e degrees of freedom. Here, γ is the significance level of the test. We chose $\gamma = 0.05$ for every case.

4.3 Summary of Model Fitting Attempts

The results of fitting the software reliability models to the data in Table 4.1.1 of Section 4.1 are summarized in Table 4.3.1. In this table, the term "fit" means that the model did not fail a chi-square goodness-of-fit test at the 0.05 level of significance, while the phrase "lack-of-fit" signifies that the model failed a chi-square goodness-of-fit test at the 0.05 level of significance. The phrase "no convergence" means that either the iterative procedures failed to converge altogether, or failed to converge to valid parameter estimates (e.g. negative N, or K>1 in the Geometric Poisson).

Obviously, since each dataset in Table 4.1.1 of Section 4.1 constitutes a unique CU and test phase, the parameter estimates are peculiar to the CU and test phase on which they are based. For example, the "N" being estimated during the IT phase for a given CU is not the same "N" being estimated during the next test phase for the same CU because errors were removed during IT.

Table 4.3.1

Summary of Model Fitting Attempts

Model	fit %*	lack of fit %*	no convergence %*
Geometric Poisson	33	25	42
Jelinski-Moranda	18	8	74
Nonhomogeneous Poisson	33	25	42
Generalized Poisson	35	10	55
IBM Poisson (Modified)	53	22	25
IBM Poisson	0	0	100
Binomial	27	16	57
Average	28.15	14.85	57.00

* Percents based on attempted fits of each model on each of 51 datasets contained in Table 4.1.1 of Section 4.1.

For the purpose of comparison, Table 4.3.2 lists the results for each dataset. In this table, the parameter estimates for each model have been used to calculate values for N and (using the conversion table 3.8.1 in Section 3.8) to allow easy comparisons between models. For the Jelinski-Moranda, Generalized Poisson, IBM Poisson and Binomial models, N is intrepreted as the number of initial errors. Analogously, for the Geometric Poisson and the Nonhomogeneous Poisson models, N is the expected number of errors to be detected in infinite time.

Each page of Table 4.3.2 represents the results of applying each model to a particular dataset identified by CPCI, CU, and PH (test phase). The total number of errors observed and removed is printed below the dataset identifier. The table entries are the estimate of N, observed errors for purposes of fitting (this number will be one less than the number printed below the dataset identifier), the estimate of ϕ, the estimate of (applies only to the Generalized Poisson and IBM Poisson Models) the observed value of the chi-square goodness-of-fit statistic, the degrees of freedom (the total number of time intervals less 1, and less the number of parameters estimated), and the 95% point of the chi-square distribution for testing goodness-of-fit.

An attempt was made to obtain fits for the four consecutive test phases IT (integration test), ST (system test), SD (independent test), and IN (installation test). In some cases, there was insufficient data to fit the models, i.e. not enough time intervals could be formed such that no errors were removed during each time interval. These cases are summarized in Table 4.3.3. Throughout, cases where there was lack of convergence are shown as entries containing asterisks in the fields, of simply by omitting the model entry for the dataset.

Appendix A gives the detailed results of the model applications including the actual parameter estimates and a table of observed versus expected number of errors for each time period.

TABLE 4.3.2: SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI CU PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
APS APC IT								
NUMBER OBS.= 35 NUMBER REMOVED= 35								
	GEOMETRIC POISSON							
		75	34	0.0056		84.9987	16	26.3011
	JELINSKI-MORANDA							
		****	34	**********		**********	16	26.3011
	NONHOMOGENEOUS POISSON							
		75	34	0.0056		84.9987	16	26.3011
	GENERALIZED POISSON							
		****	34	**********		**********	15	24.9997
	IBM POISSON (MODIFIED)							
		4355	34	0.0000		85.8949	16	26.3011
	BINOMIAL							
		****	34	**********		**********	16	26.3011
	IBM POISSON WITH VARIABLE ALPHA							
		****	34	**********		**********	15	24.9997

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI CU PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
APS APC ST								
NUMBER OBS.= 16 NUMBER REMOVED= 16								
	GEOMETRIC POISSON							
		16	15	0.1586		4.2389	3	7.8167
	JELINSKI-MORANDA							
		****	15	**********		**********	3	7.8167
	NONHOMOGENEOUS POISSON							
		16	15	0.1727		4.2389	3	7.8167
	GENERALIZED POISSON							
		****	15	**********		**********	2	5.9948
	IBM POISSON (MODIFIED)							
		****	15	**********		**********	3	7.8167
	BINOMIAL							
		17	15	0.1417		2.6718	3	7.8167
	IBM POISSON WITH VARIABLE ALPHA							
		****	15	**********		**********	2	5.9948

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI CU PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
APS APC IN								
NUMBER OBS.= 21 NUMBER REMOVED= 21								
	GEOMETRIC POISSON							
		49	20	0.0343		7.7428	5	11.0733
	JELINSKI-MORANDA							
		****	20	**********		**********	5	11.0733
	NONHOMOGENEOUS POISSON							
		49	20	0.0349		7.7428	5	11.0733
	GENERALIZED POISSON							
		21	20	0.1338	0.7964	7.9205	4	9.4917
	IBM POISSON (MODIFIED)							
		****	20	0.0000		6.9986	5	11.0733
	BINOMIAL							
		****	20	**********		**********	5	11.0733
	IBM POISSON WITH VARIABLE ALPHA							
		****	20	**********		**********	4	9.4917

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI CU PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
APS ZEZ IT								
NUMBER OBS.= 24 NUMBER REMOVED= 24								
	GEOMETRIC POISSON							
		****	23	**********		**********	7	14.0702
	JELINSKI-MORANDA							
		****	23	**********		**********	7	14.0702
	NONHOMOGENEOUS POISSON							
		****	23	**********		**********	7	14.0702
	GENERALIZED POISSON							
		28	23	0.2072	-0.1443	25.0589	6	12.5961
	IBM POISSON (MODIFIED)							
		37	23	0.0082		89.1829	7	14.0702
	BINOMIAL							
		****	23	**********		**********	7	14.0702
	IBM POISSON WITH VARIABLE ALPHA							
		****	23	**********		**********	6	12.5961

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI	CU	PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
APS	ZEZ	SD								
NUMBER OBS.= 74										
NUMBER REMOVED= 74										
			GEOMETRIC POISSON							
				155	73	0.0204		64.3555	12	21.0297
			JELINSKI-MORANDA							
				****	73	**********		**********	12	21.0297
			NONHOMOGENEOUS POISSON							
				155	73	0.0206		64.3555	12	21.0297
			GENERALIZED POISSON							

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI CU PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
APS ZEZ ST								
NUMBER OBS.= 26 NUMBER REMOVED= 26								
	GEOMETRIC POISSON							
		29	25	0.0698		10.2941	7	14.0702
	JELINSKI-MORANDA							
		****	25	**********		**********	7	14.0702
	NONHOMOGENEOUS POISSON							
		29	25	0.0723		10.2941	7	14.0702
	GENERALIZED POISSON							
		27	25	0.0606	1.1797	7.7806	6	12.5961
	IBM POISSON (MODIFIED)							
		29	25	0.0724		7.7185	7	14.0702
	BINCMIAL							
		30	25	0.0689		8.1655	7	14.0702
	IBM POISSON WITH VARIABLE ALPHA							
		****	25	**********		**********	6	12.5961

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI CU PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
APS ZEZ IN								
NUMBER OBS.= 10 NUMBER REMOVED= 10								
	GEOMETRIC POISSON							
		10	9	0.1656		3.6028	3	7.8167
	JELINSKI-MORANDA							
		****	9	**********		**********	3	7.8167
	NONHOMOGENEOUS POISSON							
		10	9	0.1810		3.6028	3	7.8167
	GENERALIZED POISSON							
		****	9	**********		**********	2	5.9948
	IBM POISSON (MODIFIED)							
		****	9	**********		**********	3	7.8167
	BINOMIAL							
		****	9	**********		**********	3	7.8167
	IBM POISSON WITH VARIABLE ALPHA							
		****	9	**********		**********	2	5.9948

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI CU PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
APS ASZ IT								
NUMBER OBS.= 58 NUMBER REMOVED= 58								
	GEOMETRIC POISSON							
		****	57	**********		**********	23	35.1779
	JELINSKI-MORANDA							
		****	57	**********		**********	23	35.1779
	NONHOMOGENEOUS POISSON							
		****	57	**********		**********	23	35.1779
	GENERALIZED POISSON							
		258	57	0.0077	0.2672	68.1667	22	33.9327
	IBM POISSON (MODIFIED)							
		8996	57	0.0000		143.0807	23	35.1779
	BINOMIAL							
		****	57	**********		**********	23	35.1779
	IBM POISSON WITH VARIABLE ALPHA							
		****	57	**********		**********	22	33.9327

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI	CU	PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
APS	ASZ	SD								

NUMBER OBS.= 20
NUMBER REMOVED= 20

MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
GEOMETRIC POISSON	22	19	0.0675		7.0142	9	16.9252
JELINSKI-MORANDA	22	19	0.0573	1	6.0026	9	16.9252
NONHOMOGENEOUS POISSON	22	19	0.0699		7.0142	9	16.9252
GENERALIZED POISSON	22	19	0.0518	1.1484	6.1032	8	15.5118
IBM POISSON (MODIFIED)	23	19	0.0586		5.9662	9	16.9252
BINOMIAL	21	19	0.0741		5.8426	9	16.9252
IBM POISSON WITH VARIABLE ALPHA	****	19	**********		**********	8	15.5118

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI	CU	PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
APS	ASZ	ST								
NUMBER OBS.= 11										
NUMBER REMOVED= 11										
			GEOMETRIC POISSON							
				****	10	**********		**********	3	7.8167
			JELINSKI-MORANDA							
				****	10	**********		**********	3	7.8167
			NONHOMOGENEOUS POISSON							
				****	10	**********		**********	3	7.8167
			GENERALIZED POISSON							
				****	10	**********		**********	2	5.9948
			IBM POISSON (MODIFIED)							
				5643	10	0.0001		2.6725	3	7.8167
			BINOMIAL							
				****	10	**********		**********	3	7.8167
			IBM POISSON WITH VARIABLE ALPHA							
				****	10	**********		**********	2	5.9948

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI CU PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
APS ACZ IT								
NUMBER OBS.= 25 NUMBER REMOVED= 25								
	GEOMETRIC POISSON							
		29	24	0.0221		32.7169	14	23.6908
	JELINSKI-MORANDA							
		****	24	**********		**********	14	23.6908
	NONHOMOGENEOUS POISSON							
		29	24	0.0223		32.7169	14	23.6908
	GENERALIZED POISSON							
		****	24	**********	**********	**********	13	22.3668
	IBM POISSON (MODIFIED)							
		****	24	**********		**********	14	23.6908
	BINOMIAL							
		****	24	**********		**********	14	23.6908
	IBM POISSON WITH VARIABLE ALPHA							
		****	24	**********		**********	13	22.3668

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI CU PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
APS ACZ ST								
NUMBER OBS.= 9								
NUMBER REMOVED= 9								
	GEOMETRIC POISSON							
		****	8	**********		**********	4	9.4917
	JELINSKI-MORANDA							
		****	8	**********		**********	4	9.4917
	NONHOMOGENEOUS POISSON							
		****	8	**********		**********	4	9.4917
	GENERALIZED POISSON							
		****	8	**********		**********	3	7.8167
	IBM POISSON (MODIFIED)							
		5476	8	0.0000		2.8649	4	9.4917
	BINOMIAL							
		****	8	**********		**********	4	9.4917
	IBM POISSON WITH VARIABLE ALPHA							
		****	8	**********		**********	3	7.8167

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI	CU	PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
APS	MMC	IT								

NUMBER OBS.= 14
NUMBER REMOVED= 14

MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
GEOMETRIC POISSON							
	****	13	**********		**********	8	15.5118
JELINSKI-MORANDA							
	****	13	**********		**********	8	15.5118
NONHOMOGENEOUS POISSON							
	****	13	**********		**********	8	15.5118
GENERALIZED POISSON							
	****	13	**********		**********	7	14.0702
IBM POISSON (MODIFIED)							
	145	13	0.0010		14.5921	8	15.5118
BINOMIAL							
	****	13	**********		**********	8	15.5118
IBM POISSON WITH VARIABLE ALPHA							
	****	13	**********		**********	7	14.0702

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI CU PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
APS MMC SD								
NUMBER OBS.= 5								
NUMBER REMOVED= 5								
	GEOMETRIC POISSON							
		5	4	0.0741		3.0736	3	7.8167
	JELINSKI-MORANDA							
		****	4	**********		**********	3	7.8167
	NONHOMOGENEOUS POISSON							
		5	4	0.0769		3.0736	3	7.8167
	GENERALIZED POISSON							
		****	4	**********		**********	2	5.9948
	IBM POISSON (MODIFIED)							
		****	4	**********		**********	3	7.8167
	BINOMIAL							
		5	4	0.0699		2.7291	3	7.8167
	IBM POISSON WITH VARIABLE ALPHA							
		****	4	**********		**********	2	5.9948

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI	CU	PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
APS	MMC	ST								
NUMBER OBS.= 14										
NUMBER REMOVED= 14										
			GEOMETRIC POISSON	17	13	0.0771		2.3219	2	5.9948
			JELINSKI-MORANDA	****	13	**********		**********	2	5.9948
			NONHOMOGENEOUS POISSON	17	13	0.0803		2.3219	2	5.9948
			GENERALIZED POISSON	****	13	**********		**********	1	3.8419
			IBM POISSON (MODIFIED)	16	13	0.0783		1.3867	2	5.9948
			BINOMIAL	17	13	0.0847		1.5927	2	5.9948
			IBM POISSON WITH VARIABLE ALPHA	****	13	**********		**********	1	3.8419

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI CU PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
APS MMC IN								
NUMBER OBS.= 27 NUMBER REMOVED= 27								
	GEOMETRIC POISSON							
		155	26	0.0121		1.1025	3	7.8167
	JELINSKI-MORANDA							
		****	26	**********		**********	3	7.8167
	NONHOMOGENEOUS POISSON							
		155	26	0.0122		1.1025	3	7.8167
	GENERALIZED POISSON							
		69	26	0.0287	0.9792	0.8083	2	5.9948
	IBM POISSON (MODIFIED)							
		****	26	0.0000		1.1423	3	7.8167
	BINOMIAL							
		****	26	**********		**********	3	7.8167
	IBM POISSON WITH VARIABLE ALPHA							
		****	26	**********		**********	2	5.9948

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI CU PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
APS ATZ IT								
NUMBER OBS.= 16 NUMBER REMOVED= 16								
	GEOMETRIC POISSON							
		****	15	**********		**********	8	15.5118
	JELINSKI-MORANDA							
		****	15	**********		**********	8	15.5118
	NONHOMOGENEOUS POISSON							
		****	15	**********		**********	8	15.5118
	GENERALIZED POISSON							
		29	15	0.0351	0.4135	3.8823	7	14.0702
	IBM POISSON (MODIFIED)							
		173	15	0.0012		12.8045	8	15.5118
	BINOMIAL							
		30	15	0.0060		23.5173	8	15.5118
	IBM POISSON WITH VARIABLE ALPHA							

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI	CU	PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
APS	ATZ	SD								

NUMBER OBS.= 13
NUMBER REMOVED= 13

MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
GEOMETRIC POISSON	****	12	**********		**********	3	7.8167
JELINSKI-MORANDA	****	12	**********		**********	3	7.8167
NONHOMOGENEOUS POISSON	****	12	**********		**********	3	7.8167
GENERALIZED POISSON	****	12	**********		**********	2	5.9948
IBM POISSON (MODIFIED)	7686	12	0.0000		7.4794	3	7.8167
BINOMIAL	****	12	**********		**********	3	7.8167
IBM POISSON WITH VARIABLE ALPHA	****	12	**********		**********	2	5.9948

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI CU PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
APS ATZ ST								
NUMBER OBS.= 7 NUMBER REMOVED= 7								
	GEOMETRIC POISSON							
		****	6	**********		**********	3	7.8167
	JELINSKI-MORANDA							
		****	6	**********		**********	3	7.8167
	NONHOMOGENEOUS POISSON							
		****	6	**********		**********	3	7.8167
	GENERALIZED POISSON							
		7	6	0.0997	1.0314	0.6998	2	5.9948
	IBM POISSON (MODIFIED)							
		7	6	0.1036		0.6690	3	7.8167
	BINOMIAL							
		****	6	**********		**********	3	7.8167
	IBM POISSON WITH VARIABLE ALPHA							

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI CU PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
APS AAZ IT								
NUMBER OBS.= 20 NUMBER REMOVED= 20								
	GEOMETRIC POISSON							
		20	19	0.0359		8.4849	9	16.9252
	JELINSKI-MORANDA							
		21	19	0.0348	1	7.6318	9	16.9252
	NONHOMOGENEOUS POISSON							
		20	19	0.0365		8.4849	9	16.9252
	GENERALIZED POISSON							
		25	19	0.0476	0.5845	5.9170	8	15.5118
	IBM POISSON (MODIFIED)							
		22	19	0.0349		6.4753	9	16.9252
	BINOMIAL							
		20	19	0.0334		8.2558	9	16.9252
	IBM POISSON WITH VARIABLE ALPHA							
		####	19	##########		##########	8	15.5118

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI CU PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
APS AAZ SD								
NUMBER OBS.= 10 NUMBER REMOVED= 10								
	GEOMETRIC POISSON							
		11	9	0.0406		11.8482	5	11.0733
	JELINSKI-MORANDA							
		10	9	0.0428	1	9.3311	5	11.0733
	NONHOMOGENEOUS POISSON							
		11	9	0.0415		11.8482	5	11.0733
	GENERALIZED POISSON							
		16	9	0.0843	0.1776	5.3483	4	9.4917
	IBM POISSON (MODIFIED)							
		11	9	0.0467		8.2715	5	11.0733
	BINOMIAL							
		10	9	0.0381		12.2701	5	11.0733
	IBM POISSON WITH VARIABLE ALPHA							
		####	9	##########		##########	4	9.4917

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI CU PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
APS AAZ ST								
NUMBER OBS.= 8 NUMBER REMOVED= 8								
	GEOMETRIC POISSON							
		****	7	**********		**********	6	12.5961
	JELINSKI-MORANDA							
		****	7	**********		**********	6	12.5961
	NONHOMOGENEOUS POISSON							
		****	7	**********		**********	6	12.5961
	GENERALIZED POISSON							
		****	7	**********		**********	5	11.0733
	IBM POISSON (MODIFIED)							
		****	7	**********		**********	6	12.5961
	BINOMIAL							
		****	7	**********		**********	6	12.5961
	IBM POISSON WITH VARIABLE ALPHA							
		****	7	**********		**********	5	11.0733

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI	CU	PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
APS	AAZ	IN								
NUMBER OBS.= 6										
NUMBER REMOVED= 6										
			GEOMETRIC POISSON							
				****	5	**********		**********	2	5.9948
			JELINSKI-MORANDA							
				****	5	**********		**********	2	5.9948
			NONHOMOGENEOUS POISSON							
				****	5	**********		**********	2	5.9948
			GENERALIZED POISSON							
				****	5	**********		**********	1	3.8419
			IBM POISSON (MODIFIED)							
				4853	5	0.0000		4.5961	2	5.9948
			BINOMIAL							
				****	5	**********		**********	2	5.9948
			IBM POISSON WITH VARIABLE ALPHA							
				****	5	**********		**********	1	3.8419

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI CU PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
APS MEZ IT								
NUMBER OBS.= 30 NUMBER REMOVED= 30								
	GEOMETRIC POISSON							
		34	29	0.0221		76.8464	12	21.0297
	JELINSKI-MORANDA							
		33	29	0.0224	1	63.5094	12	21.0297
	NONHOMOGENEOUS POISSON							
		34	29	0.0223		75.8464	12	21.0297
	GENERALIZED POISSON							
		35	29	0.1111	0.0505	15.4207	11	19.6806
	IBM POISSON (MODIFIED)							
		****	29	**********		**********	12	21.0297
	BINOMIAL							
		****	29	**********		**********	12	21.0297
	IBM POISSON WITH VARIABLE ALPHA							
		****	29	**********		**********	11	19.6806

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI	CU	PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
APS	MEZ	SD								
NUMBER OBS.= 10										
NUMBER REMOVED= 10										
			GEOMETRIC POISSON							
				****	9	**********		**********	4	9.4917
			JELINSKI-MORANDA							
				****	9	**********		**********	4	9.4917
			NONHOMOGENEOUS POISSON							
				****	9	**********		**********	4	9.4917
			GENERALIZED POISSON							
				16	9	0.1967	-0.3098	1.1372	3	7.8167
			IBM POISSON (MODIFIED)							
				10	9	0.1711		5.7030	4	9.4917
			BINOMIAL							
				****	9	**********		**********	4	9.4917
			IBM POISSON WITH VARIABLE ALPHA							

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI CU PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
APS MEZ ST								
NUMBER OBS.= 8								
NUMBER REMOVED= 8								
	GEOMETRIC POISSON							
		****	7	**********		**********	3	7.8167
	JELINSKI-MORANDA							
		****	7	**********		**********	3	7.8167
	NONHOMOGENEOUS POISSON							
		****	7	**********		**********	3	7.8167
	GENERALIZED POISSON							
		****	7	**********		**********	2	5.9948
	IBM POISSON (MODIFIED)							
		8	7	0.1354		1.0532	3	7.8167
	BINOMIAL							
		****	7	**********		**********	3	7.8167
	IBM POISSON WITH VARIABLE ALPHA							

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI	CU	PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
APS	HTZ	IT								

NUMBER OBS.= 12
NUMBER REMOVED= 12

MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
GEOMETRIC POISSON	****	11	**********		**********	6	12.5961
JELINSKI-MORANDA	****	11	**********		**********	6	12.5961
NONHOMOGENEOUS POISSON	****	11	**********		**********	6	12.5961
GENERALIZED POISSON	153	11	0.0077	0.1493	2.9590	5	11.0733
IBM POISSON (MODIFIED)	3898	11	0.0001		11.0256	6	12.5961
BINOMIAL	****	11	**********		**********	6	12.5961
IBM POISSON WITH VARIABLE ALPHA	****	11	**********		**********	5	11.0733

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI CU PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
APS HTZ SD								
NUMBER OBS.= 21 NUMBER REMOVED= 21								
	GEOMETRIC POISSON							
		22	20	0.0994		37.4639	4	9.4917
	JELINSKI-MORANDA							
		****	20	**********		**********	4	9.4917
	NONHOMOGENEOUS POISSON							
		22	20	0.1046		37.4639	4	9.4917
	GENERALIZED POISSON							
		****	20	**********	**********	**********	3	7.8167
	IBM POISSON (MODIFIED)							
		****	20	**********		**********	4	9.4917
	BINOMIAL							
		****	20	**********		**********	4	9.4917
	IBM POISSON WITH VARIABLE ALPHA							
		****	20	**********		**********	3	7.8167

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI CU PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
APS HTZ ST								
NUMBER OBS.= 16 NUMBER REMOVED= 16								
	GEOMETRIC POISSON							
		16	15	0.0749		1.8858	6	12.5961
	JELINSKI-MORANDA							
		17	15	0.0705	1	0.5711	6	12.5961
	NONHOMOGENEOUS POISSON							
		16	15	0.0778		1.8858	6	12.5961
	GENERALIZED POISSON							
		16	15	0.0567	1.2532	0.2643	5	11.0733
	IBM POISSON (MODIFIED)							
		17	15	0.0698		0.9204	6	12.5961
	BINOMIAL							
		17	15	0.0805		1.2172	6	12.5961
	IBM POISSON WITH VARIABLE ALPHA							
		****	15	**********		**********	5	11.0733

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI	CU	PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
APS	MIZ	IT								

NUMBER OBS.= 18
NUMBER REMOVED= 18

MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
GEOMETRIC POISSON							
	****	17	**********		**********	7	14.0702
JELINSKI-MORANDA							
	****	17	**********		**********	7	14.0702
NONHOMOGENEOUS POISSON							
	****	17	**********		**********	7	14.0702
GENERALIZED POISSON							
	****	17	**********		**********	6	12.5961
IBM POISSON (MODIFIED)							
	8451	17	0.0000		14.2827	7	14.0702
BINOMIAL							
	****	17	**********		**********	7	14.0702
IBM POISSON WITH VARIABLE ALPHA							
	****	17	**********		**********	6	12.5961

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI	CU	PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
APS	MIZ	SD								

NUMBER OBS.= 28
NUMBER REMOVED= 28

MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
GEOMETRIC POISSON							
	28	27	0.0629		15.5187	10	18.3111
JELINSKI-MORANDA							
	28	27	0.0565	1	12.1115	10	18.3111
NONHOMOGENEOUS POISSON							
	28	27	0.0649		15.5187	10	18.3111
GENERALIZED POISSON							

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI	CU	PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
APS	MIZ	ST								

NUMBER OBS.= 16
NUMBER REMOVED= 16

MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
GEOMETRIC POISSON							
	****	15	**********		**********	7	14.0702
JELINSKI-MORANDA							
	****	15	**********		**********	7	14.0702
NONHOMOGENEOUS POISSON							
	****	15	**********		**********	7	14.0702
GENERALIZED POISSON							
	16	15	0.1695	0.5192	2.7711	6	12.5961
IBM POISSON (MODIFIED)							
	16	15	0.1645		3.4519	7	14.0702
BINOMIAL							
	****	15	**********		**********	7	14.0702
IBM POISSON WITH VARIABLE ALPHA							

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI	CU	PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
APS	DAZ	IT								
NUMBER OBS.= 60										
NUMBER REMOVED= 61										
			GEOMETRIC POISSON							
				62	59	0.0528		31.6067	15	24.9997
			JELINSKI-MORANDA							
				62	59	0.0470	1	22.9963	15	24.9997
			NONHOMOGENEOUS POISSON							
				62	59	0.0542		31.6067	15	24.9997
			GENERALIZED POISSON							
				****	59	**********	**********	**********	14	23.6908
			IBM POISSON (MODIFIED)							
				63	59	0.0490		23.2293	15	24.9997
			BINOMIAL							
				64	59	0.0521		24.7596	15	24.9997
			IBM POISSON WITH VARIABLE ALPHA							
				****	59	**********		**********	14	23.6908

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI CU PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
APS DAZ SD								
NUMBER OBS.= 31 NUMBER REMOVED= 31								
	GEOMETRIC POISSON	31	30	0.0710		11.7709	9	16.9252
	JELINSKI-MORANDA	31	30	0.0520	1	9.0968	9	16.9252
	NONHOMOGENEOUS POISSON	31	30	0.0736		11.7709	9	16.9252
	GENERALIZED POISSON	33	30	0.0777	0.6543	5.3252	8	15.5118
	IBM POISSON (MODIFIED)	****	30	**********		**********	9	16.9252
	BINOMIAL	32	30	0.0604		11.5401	9	16.9252
	IBM POISSON WITH VARIABLE ALPHA	****	30	**********		**********	8	15.5118

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI	CU	PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
APS	DAZ	ST								

NUMBER OBS.= 27
NUMBER REMOVED= 27

MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
GEOMETRIC POISSON	29	26	0.0731		11.7299	11	19.6806
JELINSKI-MORANDA	****	26	**********		**********	11	19.6806
NONHOMOGENEOUS POISSON	29	26	0.0760		11.7299	11	19.6806
GENERALIZED POISSON	****	26	**********		**********	10	18.3111
IBM POISSON (MODIFIED)	27	26	0.0804		10.4038	11	19.6806
BINOMIAL	29	26	0.0765		9.5557	11	19.6806
IBM POISSON WITH VARIABLE ALPHA	****	26	**********		**********	10	18.3111

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI CU PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
APS DAZ IN								
NUMBER OBS.= 9								
NUMBER REMOVED= 9								
	GEOMETRIC POISSON							
		13	8	0.0614		4.2929	5	11.0733
	JELINSKI-MORANDA							
		****	8	**********		**********	5	11.0733
	NONHOMOGENEOUS POISSON							
		13	8	0.0633		4.2929	5	11.0733
	GENERALIZED POISSON							
		****	8	**********	**********	**********	4	9.4917
	IBM POISSON (MODIFIED)							
		10	8	0.0900		4.4900	5	11.0733
	BINOMIAL							
		16	8	0.0523		3.5982	5	11.0733
	IBM POISSON WITH VARIABLE ALPHA							
		****	8	**********		**********	4	9.4917

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI CU PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
APS SAD IT								
NUMBER OBS.= 51 NUMBER REMOVED= 51								
	GEOMETRIC POISSON							
		51	50	0.0616		47.7485	13	22.3668
	JELINSKI-MORANDA							
		51	50	0.0581	1	39.1583	13	22.3668
	NONHOMOGENEOUS POISSON							
		51	50	0.0636		47.7485	13	22.3668
	GENERALIZED POISSON							
		57	50	0.1044	0.1874	13.8245	12	21.0297
	IBM POISSON (MODIFIED)							
		52	50	0.0666		30.4158	13	22.3668
	BINOMIAL							
		51	50	0.0441		66.3159	13	22.3668
	IBM POISSON WITH VARIABLE ALPHA							
		****	50	**********		**********	12	21.0297

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI CU PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
APS SAD SD								
NUMBER OBS.= 52 NUMBER REMOVED= 52								
	GEOMETRIC POISSON							
		52	51	0.0925		21.9550	14	23.6908
	JELINSKI-MORANDA							
		53	51	0.0709	1	16.6943	14	23.6908
	NONHOMOGENEOUS POISSON							
		52	51	0.0970		21.9550	14	23.6908
	GENERALIZED POISSON							
		52	51	0.0593	1.2998	17.1907	13	22.3668
	IBM POISSON (MODIFIED)							
		****	51	**********		**********	14	23.6908
	BINOMIAL							
		53	51	0.0978		17.1500	14	23.6908
	IBM POISSON WITH VARIABLE ALPHA							
		****	51	**********		**********	13	22.3668

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI	CU	PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
APS	SAD	ST								

NUMBER OBS.= 20
NUMBER REMOVED= 20

MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
GEOMETRIC POISSON	24	19	0.0719		13.6776	7	14.0702
JELINSKI-MORANDA	****	19	**********		**********	7	14.0702
NONHOMOGENEOUS POISSON	24	19	0.0747		13.6776	7	14.0702
GENERALIZED POISSON	21	19	0.0640	1.3144	14.3756	6	12.5961
IBM POISSON (MODIFIED)	23	19	0.0789		13.2103	7	14.0702
BINOMIAL	21	19	0.1054		10.5990	7	14.0702
IBM POISSON WITH VARIABLE ALPHA	****	19	**********		**********	6	12.5961

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI	CU	PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
APS	ZBZ	IT								
NUMBER OBS.= 21										
NUMBER REMOVED= 21										
			GEOMETRIC POISSON							
				21	20	0.0617		15.8781	7	14.0702
			JELINSKI-MORANDA							
				21	20	0.0501	1	8.0144	7	14.0702
			NONHOMOGENEOUS POISSON							
				21	20	0.0637		15.8781	7	14.0702
			GENERALIZED POISSON							
				21	20	0.0299	1.2839	10.6501	6	12.5961
			IBM POISSON (MODIFIED)							
				22	20	0.0552		8.7739	7	14.0702
			BINOMIAL							
				22	20	0.0660		12.4096	7	14.0702
			IBM POISSON WITH VARIABLE ALPHA							
				****	20	**********		**********	6	12.5961

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI	CU	PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
APS	ZBZ	SD								
NUMBER OBS.= 80										
NUMBER REMOVED= 80										
			GEOMETRIC POISSON							
				87	79	0.0591		35.7130	14	23.6908
			JELINSKI-MORANDA							
				85	79	0.0520	1	28.4206	14	23.6908
			NONHOMOGENEOUS POISSON							
				87	79	0.0609		35.7130	14	23.6908
			GENERALIZED POISSON							
				85	79	0.0722	0.7128	22.8874	13	22.3668
			IBM POISSON (MODIFIED)							
				85	79	0.0568		26.3029	14	23.6908
			BINOMIAL							
				93	79	0.0476		36.6033	14	23.6908
			IBM POISSON WITH VARIABLE ALPHA							
				****	79	**********		**********	13	22.3668

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI	CU	PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
APS	ZBZ	ST								

NUMBER OBS.= 42
NUMBER REMOVED= 42

MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
GEOMETRIC POISSON	47	41	0.0723		24.1808	10	18.3111
JELINSKI-MORANDA	****	41	**********		**********	10	18.3111
NONHOMOGENEOUS POISSON	47	41	0.0750		24.1808	10	18.3111
GENERALIZED POISSON	****	41	**********		**********	9	16.9252
IBM POISSON (MODIFIED)	44	41	0.0803		23.9890	10	18.3111
BINOMIAL	45	41	0.0873		21.5964	10	18.3111
IBM POISSON WITH VARIABLE ALPHA	****	41	**********		**********	9	16.9252

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI	CU	PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
DRS	DAD	IT								
NUMBER OBS.= 20										
NUMBER REMOVED= 20										
			GEOMETRIC POISSON	21	19	0.0299		34.2803	9	16.9252
			JELINSKI-MORANDA	****	19	**********		**********	9	16.9252
			NONHOMOGENEOUS POISSON	21	19	0.0303		34.2803	9	16.9252
			GENERALIZED POISSON	****	19	**********		**********	8	15.5118
			IBM POISSON (MODIFIED)	21	19	0.0307		25.3871	9	16.9252
			BINOMIAL	20	19	0.0391		19.7285	9	16.9252
			IBM POISSON WITH VARIABLE ALPHA	****	19	**********		**********	8	15.5118

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI	CU	PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
OSS	LDR	SD								

NUMBER OBS.= 28
NUMBER REMOVED= 28

MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
GEOMETRIC POISSON	****	27	**********		**********	9	16.9252
JELINSKI-MORANDA	****	27	**********		**********	9	16.9252
NONHOMOGENEOUS POISSON	****	27	**********		**********	9	16.9252
GENERALIZED POISSON	****	27	**********		**********	8	15.5118
IBM POISSON (MODIFIED)	****	27	**********		**********	9	16.9252
BINOMIAL	****	27	**********		**********	9	16.9252
IBM POISSON WITH VARIABLE ALPHA	****	27	**********		**********	8	15.5118

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI CU PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
OSS LDR ST								
NUMBER OBS.= 11 NUMBER REMOVED= 11								
	GEOMETRIC POISSON							
		****	10	**********		**********	6	12.5961
	JELINSKI-MORANDA							
		****	10	**********		**********	6	12.5961
	NONHOMOGENEOUS POISSON							
		****	10	**********		**********	6	12.5961
	GENERALIZED POISSON							
		****	10	**********		**********	5	11.0733
	IBM POISSON (MODIFIED)							
		2762	10	0.0001		2.2529	6	12.5961
	BINOMIAL							
		****	10	**********		**********	6	12.5961
	IBM POISSON WITH VARIABLE ALPHA							

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI CU PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
SES VAS IT								
NUMBER OBS.= 14 NUMBER REMOVED= 14								
	GEOMETRIC POISSON	20	13	0.0308		13.2579	8	15.5118
	JELINSKI-MORANDA	****	13	**********		**********	8	15.5118
	NONHOMOGENEOUS POISSON	20	13	0.0313		13.2579	8	15.5118
	GENERALIZED POISSON	****	13	**********		**********	7	14.0702
	IBM POISSON (MODIFIED)	5231	13	0.0000		12.0299	8	15.5118
	BINOMIAL	19	13	0.0313		13.3687	8	15.5118
	IBM POISSON WITH VARIABLE ALPHA	****	13	**********		**********	7	14.0702

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI CU PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
SES VAS SD								
NUMBER OBS.= 20 NUMBER REMOVED= 20								
	GEOMETRIC POISSON							
		****	19	**********		**********	9	16.9252
	JELINSKI-MORANDA							
		****	19	**********		**********	9	16.9252
	NONHOMOGENEOUS POISSON							
		****	19	**********		**********	9	16.9252
	GENERALIZED POISSON							
		****	19	**********		**********	8	15.5118
	IBM POISSON (MODIFIED)							
		3268	19	0.0001		21.5292	9	16.9252
	BINOMIAL							
		****	19	**********		**********	9	16.9252
	IBM POISSON WITH VARIABLE ALPHA							
		****	19	**********		**********	8	15.5118

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI CU PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
SES VAS ST								
NUMBER OBS.= 5 NUMBER REMOVED= 5								
	GEOMETRIC POISSON							
		****	4	**********		**********	2	5.9948
	JELINSKI-MORANDA							
		****	4	**********		**********	2	5.9948
	NONHOMOGENEOUS POISSON							
		****	4	**********		**********	2	5.9948
	GENERALIZED POISSON							
		****	4	**********		**********	1	3.8419
	IBM POISSON (MODIFIED)							
		****	4	**********		**********	2	5.9948
	BINOMIAL							
		****	4	**********		**********	2	5.9948
	IBM POISSON WITH VARIABLE ALPHA							

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI CU PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
SUS CON IT								
NUMBER OBS.= 30 NUMBER REMOVED= 30								
	GEOMETRIC POISSON							
		****	29	**********		**********	13	22.3668
	JELINSKI-MORANDA							
		****	29	**********		**********	13	22.3668
	NONHOMOGENEOUS POISSON							
		****	29	**********		**********	13	22.3668
	GENERALIZED POISSON							
		****	29	**********		**********	12	21.0297
	IBM POISSON (MODIFIED)							
		3269	29	0.0000		129.4443	13	22.3668
	BINOMIAL							
		****	29	**********		**********	13	22.3668
	IBM POISSON WITH VARIABLE ALPHA							
		****	29	**********		**********	12	21.0297

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI CU PH: SUS CON SD

NUMBER OBS.= 11
NUMBER REMOVED= 11

MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
GEOMETRIC POISSON	****	10	**********		**********	3	7.8167
JELINSKI-MORANDA	****	10	**********		**********	3	7.8167
NONHOMOGENEOUS POISSON	****	10	**********		**********	3	7.8167
GENERALIZED POISSON	84	10	0.0058	0.9162	4.2390	2	5.9948
IBM POISSON (MODIFIED)	39	10	0.0113		4.3615	3	7.8167
BINOMIAL	****	10	**********		**********	3	7.8167
IBM POISSON WITH VARIABLE ALPHA	****	10	**********		**********	2	5.9948

TABLE 4.3.2 (CONTINUED): SUMMARY OF MODEL PARAMETER ESTIMATION RESULTS

CPCI	CU	PH	MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
SUS	CON	ST								

NUMBER OBS.= 12
NUMBER REMOVED= 12

MODEL	EST N	OBS ERRORS	PHI	ALPHA	OBSERVED CHI-SQUARE	DEG FREE	CRITICAL CHI-SQUARE
GEOMETRIC POISSON	12	11	0.0503		25.5949	8	15.5118
JELINSKI-MORANDA	12	11	0.0447	1	25.4756	8	15.5118
NONHOMOGENEOUS POISSON	12	11	0.0516		25.5949	8	15.5118
GENERALIZED POISSON	16	11	0.0718	0.3152	15.1733	7	14.0702
IBM POISSON (MODIFIED)	13	11	0.0444		23.3377	8	15.5118
BINOMIAL	12	11	0.0506		20.8185	8	15.5118
IBM POISSON WITH VARIABLE ALPHA	****	11	**********		**********	7	14.0702

Table 4.3.3

Datasets with Insufficient Data

CPCI	CU	PH	ERRORS DETECTED	ERRORS REMOVED
APS	APC	SD	4	4
APS	ASZ	IN	2	2
APS	ACZ	SD	4	4
APS	ACZ	IN	2	2
APS	ATZ	IN	2	2
APS	MEZ	IN	3	3
APS	HTZ	IN	7	7
APS	MIZ	IN	5	5
APS	SAD	IN	2	2
APS	ZBZ	IN	4	4
DRS	DAD	SD	3	3
DRS	DAD	ST	4	4
DRS	DAD	IN	2	2
OSS	LDR	IT	7	7
OSS	LDR	IN	3	3
SES	VAS	IN	2	2
SUS	CON	IN	2	2

4.4 Discussion of Results

The overall success of applying the models is summarized in Table 4.3.1 of Section 4.3. The highest percentage of good fits was achieved by the IBM Poisson model (modified as discussed in Section 3.4) with 53% of the attempts resulting in fits (a "passed" goodness-of-fit test). Of the cases where convergence was achieved, roughly 71% of the attempts led to good fits for the modified IBM Poisson Model. In direct contrast, the unmodified, three parameter IBM Poisson Model experienced no success with 100% of the attempts resulting in failure of the parameter estimating algorithms to converge. The Geometric Poisson, Nonhomogeneous Poisson, Generalized Poisson, and Binomial Models experienced roughly the same success rates, while the modified Jelinski-Moranda model had the second to lowest success rate at 18%.

The comparatively poor performance of the Jelinski-Moranda model is also indicative of the failure of the Imperfect Debugging model in view of the similarities between these two models. Table 4.4.1 gives a rank ordering of the models by success rate. We caution that "success" means that the model parameter estimator algorithms converged <u>and</u> a good fit was obtained (i.e. the chi-square test was not failed). Thus, since failure of the parameter estimating algorithms to converge is not necessarily due to failure of the model to be valid (i.e. it could be due to lack of starting points for the iterations) the rank ordering can be misleading. For example, the IBM Poisson model is ranked highest with a 53% success rate, while the Jelinski-Moranda model is second to lowest with 18% success rate. However, if only cases where convergence was obtained are considered, the ranking would be headed by the Generalized Poisson Model (78%) followed by the modified IBM Poisson model (71%), the Jelinski-Moranda model (69%), the Binomial model (64%), and the Geometric Poisson and Nonhomogeneous Poisson models (both at 57%). That the Generalized Poisson model has the highest percentage of good fits for cases in which convergence was obtained was to be expected since this model has three parameters and thus more flexibility to fit.

That the IBM Poisson model (modified) showed the highest overall success rate of 53% is also a little misleading. Referring to Table 4.3.2, in nine of the instances where a good fit was obtained for this model, ridiculously large values for N were reported (e.g. 5,643 for APS ASZ ST) while extremely small values for ϕ were reported. These cases reflected an identifiability problem in the model, i.e. the data did not show enough structure to allow identification of both parameters N and ϕ. If these cases are not counted as good fits, then the overall success rate would be 35% rather than 53%.

Table 4.4.1

Model Success Percentages

Model	Success Percentage	Percentage of Good Fits When Convergence Was Achieved
IBM Poisson (modified)	53	71
Generalized Poisson	35	78
Nonhomogeneous Poisson	33	57
Geometric Poisson	33	57
Binomial	27	64
Jelinski-Moranda	18	69
IBM Poisson	0	-

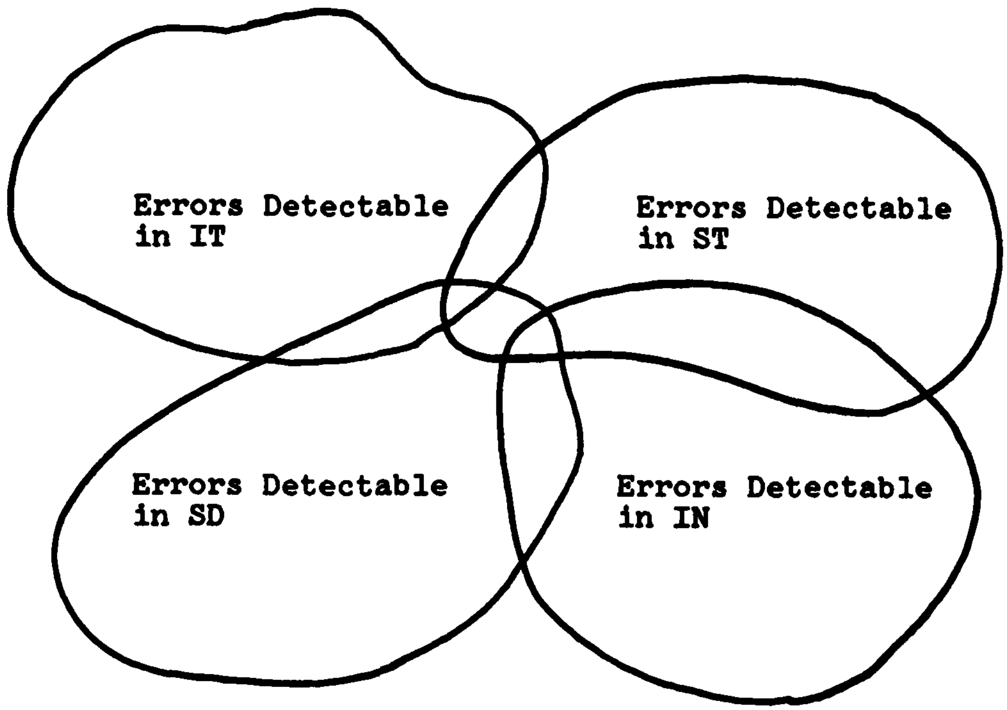
It is interesting to note that the similarities noted in Section 3.8 have manifested themselves in Table 4.3.2 of Section 4.3. That is, in nearly every instance where the majority of the six models (Geometric Poisson, Jelinski-Moranda, Nonhomogeneous Poisson, Generalized Poisson, IBM Poisson, and Binomial) showed success, the estimates of N and ϕ were very close. Moreover, the equivalence of the Nonhomogeneous Poisson and Geometric Poisson Models is evident; every instance in which these two models' parameter estimating procedures converged, the same value for N was obtained (see Table 3.8.1) and the correspondence in equations (3.8.6) held. In view of this correspondence it is not surprising that the success percent was the same for both models.

Another important result to be inferred from Table 4.3.2 of Section 4.3 is related to the test phase dependence of the models. Earlier we discussed the fact that testing intensity and methodology are roughly constant within a test phase, but differ markedly between test phases. Moreover, it is conceivable that the possible types of errors which can be detected during different test phases varies with test phase as depicted in Figure 4.4.1. This is a plausible explanation for the fact that often in Table 4.3.2, the number of errors detected in one test phase greatly exceeds the estimated residual number of errors predicted by a model (one that fits) in the previous test phase. For example, in the case of CPCI APS, CU AAZ, the Generalized Poisson Model was a good fit (a chi-square observed as 5.917 on 8 degrees of freedom) for the data from the IT (integration test) phase. The initial number of errors was estimated to be 25. Since 20 errors were removed, the estimated number of residual errors would be 5. During the next test phase, SD (independent test) 10 addition errors were removed; twice as many as the estimated number of residual errors from the previous phase. Once again, the Generalized Poisson Model was a good fit on the SD phase data, estimating N to be 16, leaving 6 as the estimated number of residual errors. The subsequent number of errors removed during the ST (system test) and IN (installation test) phases was 8 + 6 = 14, more than twice the estimated number of residual errors estimated during SD. Examples similar to this abound in Table 4.3.2 of Section 4.3. These examples do not, by themselves, indicate that the software reliability models are inadequate. Rather, they support the conjecture that each test phase is capable of detecting its own (possibly unique) class of errors. They also, however, support the unfortunate conclusion that the models are of no use in general for predicting errors from future test phases. Table 4.4.2 gives the comparisons of estimated residual errors and errors actually removed for each model and CU for which at least two of the test phases (IT, SD, ST, and IN) resulted in good fits.

It is not surprising that the overwelming majority of fits obtained were from CUs in APS since APS generated the most errors (nearly 4 times the number from its nearest competitor, OSS). As mentioned in Section 2.6, the highest error rates per module were achieved by APS and OSS where the percent of "lifted" design was more balanced with the percent of newly developed code. We are not able to draw any conclusions concerning the relationship between newly developed design percent and the tendency of the models to fit because the data from the other CPCIs is so sparse.

Figure 4.4.1

Error Detectability Over Test Phase



IT = Integration Test

ST = System Test

SD = Independent Test

IN = Installation Test

TABLE 4.4.2. MODEL PREDICTIONS FOR CPCI APS

Test Phase

		IT		SD		ST		IN	
**Model	CU	Residual Errors	Errors Removed	Residual Errors	Errors Removed	Residual Errors	Errors Removed	Residual Errors	Errors Removed
Geo.	APC	*	35	*	4	0	16	28	21
NP	APC	*	35	*	4	0	16	28	21
Geo.	ZEZ	*	24	*	74	3	26	0	10
NP	ZEZ	*	24	*	74	3	26	0	10
GP	ASZ	*	58	2	20	*	11	*	2
IBM	ASZ	*	58	3	20	5632	11	*	2
Geo.	MMC	*	14	0	5	3	14	128	27
NP	MMC	*	14	0	5	3	14	128	27
IBM	MMC	131	14	*	5	2	14	*	27

TABLE 4.4.2. MODEL PREDICTIONS FOR CPCI APS (Continued)

		Test Phase							
		IT		SD		ST		IN	
**Model	CU	Residual Errors	Errors Removed	Residual Errors	Errors Removed	Residual Errors	Errors Removed	Residual Errors	Errors Removed
BIN	MMC	*	14	0	5	3	14	*	27
GP	ATZ	13	16	*	13	0	7	*	2
IBM	ATZ	157	16	7673	13	13	7	0	2
JM	AAZ	1	20	0	10	*	8	*	6
NP	AAZ	0	20	1	10	*	8	*	6
GP	AAZ	5	20	6	10	*	8	*	6
IBM	AAZ	2	20	1	10	*	8	4847	6
BIN	AAZ	0	20	0	10	*	8	*	6
GP	MEZ	5	30	6	10	*	8	*	3

TABLE 4.4.2. MODEL PREDICTIONS FOR CPCI APS (Continued)

		Test Phase							
		IT		SD		ST		IN	
**Model	CU	Residual Errors	Errors Removed	Residual Errors	Errors Removed	Residual Errors	Errors Removed	Residual Errors	Errors Removed
IBM	MEZ	*	30	0	10	0	8	*	3
Geo.	HTZ	*	12	*	21	0	16	*	7
GP	HTZ	141	12	*	21	0	16	*	7
IBM	HTZ	3886	12	*	21	1	16	*	7
Geo.	DAZ	*	60	0	31	2	27	4	9
JM	DAZ	2	60	0	31	*	27	*	9
NP	DAZ	*	60	0	31	2	27	4	9
IBM	DAZ	3	60	*	31	0	27	1	9
BIN	DAZ	4	60	1	31	2	27	7	9
Geo.	SAD	*	51	0	52	4	20	*	2

TABLE 4.4.2. MODEL PREDICTIONS FOR CPCI APS (Continued)

Test Phase

		IT		SD		ST		IN	
**Model	CU	Residual Errors	Errors Removed	Residual Errors	Errors Removed	Residual Errors	Errors Removed	Residual Errors	Errors Removed
NP	SAD	*	51	0	52	4	20	*	2
GP	SAD	6	51	0	52	*	20	*	2
BIN	SAD	*	51	1	52	1	20	*	2

* Model failed goodness-of-fit test or parameter estimates failed to converge

** Geo. - Geometric Poisson Model

JM - Jelinski-Moranda

NP - Nonhomogeneous Poisson Model

GP - Generalized Poisson Model

IBM - Modified IBM Model

BIN - Binomial Model

5. CONCLUSIONS AND RECOMMENDATIONS

5.1 Software Error Data Collection

The software error data collection guidelines proposed in Section 2.4 are sound and should be applicable to any C^3I software project on which high quality data on software errors is needed. An error data collection system like the one employed in collecting the JSS data is relatively inexpensive to implement (about 0.6% of the overall software development effort on JSS) and use, and provides the requisite input data for the software reliability models (except for the Imperfect Debugging Model in its original form) described in this report. Whether or not the data is used for fitting these software reliabilty models, such a database can be an invaluable source of historical data to aid in both the project and acquisition manager's decision processes.

It is however, important to note some characteristics of a database compiled like the JSS database in relation to the assumptions made in many software reliability models. First, the data is "coarse" in the sense that the time scale is calendar time and the dates when errors are detected (and, resolved and verified) can be determined only to the week. However, on a project the size of JSS, keeping track of execution time, for example, would have severely perturbed the project in general.

Secondly, software testing does not cease when an error is detected and resume when the error is removed. Such a requirement would severely delay the development of a large scale project like JSS. This assumption is commonly made in the original forms of many software reliability models.

Thirdly, the time to remcve an error is almost never "negligible", (another assumption commonly made in software reliability modelling).

Next, all the software is not under test at all times. In fact, not all the software in a given module is under test when the module is under test. This is in direct violation to the assumptions (either implicit or explicit) of all the software reliability models studied here.

Finally, calendar time is not necessarily representative of debugging time in view of varying manpower, testing intensity (test phase), and schedule milestones. Thus, any time-dependent figures-of-merit derived from any of the software reliability models must be suspect if used to represent the operational scenario of the software.

It is the opinion of many software managers at Hughes that to "upgrade" the software error data collection efforts on

large projects to meet the assumptions of the software reliability models (in their original, unmodified forms) would incur unreasonable costs; costs which could better be spent during software design. We believe that a database (like JSS) developed within the guidelines proposed in Section 2.4, provides the best software error data to be expected within a reasonable budget, does not result in project delays, and is relatively easy to manage. That it would not be ideally suited for software reliability modelling is neither surprising nor disturbing, for the majority of the data collection system on which it is based was developed long before software reliability models emerged, and therefore not with software reliability prediction as its purpose. Nevertheless, the data collected under this system will accommodate most of the current models, and before major changes to this data collection system are undertaken, a definitive software reliability modeling methodology must be developed. In view of these considerations, we recommend that software error data on large C^3I projects be collected as described in Section 2.4 and that future attempts at validating a definitive software reliability model be performed on small-scale, ad hoc computer programs (as done by Nagel and Skrivan (1982)). In addition, we recommend that for large C3I projects, that manpower loading in the software debugging effort be continuously monitored, and that the exact date at which each unit of software begins each new test phase be recorded. When a definitive software reliability model is discovered under these circumstances, then the issue of more comprehensive data collection on the larger-scale C^3I projects can be effectively and economically addressed.

5.2 Software Reliability Models and Guidelines for their Use by Software Acquisition Managers.

Early in the course of this study we discovered that several of the important assumptions made by the software reliability models considered in this study are not valid for the JSS project, and probably not true in general. Also, disappointingly, the prospect of collecting the times between error detections was dismissed early as impractical, making the use of the original Imperfect Debugging Model impossible (the Jelinski-Moranda model was used instead because of its similarity to the Imperfect Debugging Model). These assumptions which are violated have been pointed out in the text of this report. Some of them are of a mathematical nature (e.g. each error occurs with the same rate) and some are related to the data collection (e.g. that each error is immediately removed when detected or that removal time is negligible, testing stops while the error is removed, testing is uniform, all the software is being tested, etc). By restricting model fitting attempts to single compilation units (CUs) and test phases, and modifying some of the models, we alleviated most of the violations relating to data collection and thus provided these models a better chance to fit the JSS data. Indeed, there would have been no point in fitting the models in their original form to all the JSS data at once since they were

clearly not valid for the JSS data overall. The models which were modified mathematically were the IBM Poisson Model, and the Geometric Poisson Model. Only for the IBM Poisson Model could both the original and modified versions be utilized, and the result was that the modified version showed the highest percent of good fits over all models, while the original version failed in every attempt to achieve parameter estimates.

In spite of modifications and careful use of the JSS data, the models performed very poorly overall with respect to application to the JSS data. In particular, lack of convergence of the iterative procedures for estimating the parameters or the failure of chi-square goodness-of-fit tests at the 0.05 significance level was the rule, rather than the exception.

The similarities which exist among the models are surprising. Roughly speaking, they are all slight variations on the same theme; that theme being constant and equal single error occurrence rate, and that the expected number of errors to be detected in a time interval is proportional to the number of errors remaining or "at risk". In fact, the Geometric Poisson Model (as derived in this report to handle unequal time intervals) was shown to be equivalent to the Nonhomogeneous Poisson Model when the time intervals are of integer length. A quantitative assessment of how similar the models are is offered in Table 4.3.2 of Section 4.3. That is, when all the models fit a particular dataset, the estimates they provided for the initial number of errors (or expected number of errors detectable in infinite time, as appropriate) were not substantially different, and often equal.

We found that residual errors (or expected residual errors, as the case may be) would be the most appropriate reliability measure to project personnel because of its time scale independence. Other time-dependent figures-of-merit can be misleading when based on a model fit to calendar time data since calendar time is not uniformly representative of test phase time nor system operation time.

As far as the predictive capability of the models, the evidence suggests that the models cannot predict the number of residual errors detectable in future test phases. The failure of the models to accurately predict the number of errors remaining was so dramatic, in fact, that detailed statistical analyses of these predictions were not necessary. The explanation for this is not necessarily the failure of the models and their assumptions. Rather, we believe that this failure is partly due to the fact that different test phases for software can detect their own different (often dramatically different) classes of errors. While these classes obviously overlap, they can be very different indeed. For example, some errors in module interfaces may not be detectable prior to parameter and assembly testing, some errors in software subsystem functions cannot all be detected prior to

independent testing, and so on. Thus, since the models are ignorant of this possibility, results obtained from data prior to a given test phase can have very little predictive capability pertaining to that test phase. On the other hand, the results of fitting the models within a single test phase appeared to be consistent with the errors detected and removed within that test phase, whenever the models passed the goodness-of-fit test.

Perhaps the most damaging aspects of the models from the point of view of the acquisition manager are the numerical difficulties encountered in applying the models. The issues concerning starting points for the iterative procedures, uniqueness of the estimates, and even alternative estimation techniques must be studied and such problems solved before these models can be used by acquisition managers.

From the point of view of the Software Acquisition Manager, the overwelming difficulty in applying and obtaining good fits with these models on the JSS data should discourage their use by contractual requirement. However, if in spite of the evidence presented in this study pertaining to the lack of applicability of the models to the JSS data, it is determined that one of these models must be used, we recommend the following guidelines for their use:

a) Collect data according to the guidelines in Section 2.4.

b) Apply the model at the compilation unit level.

c) Apply the model to data within a single test phase, and interpret the results in the context of that test phase only.

d) Use the results to decide if more testing within that phase is necessary.

e) Do not use the results of a model if, in fitting the model, it fails the chi-square goodness-of-fit test at an appropriate level of significance (we recommend 0.05).

Guideline d) deserves some comment. We believe that the best use of one of these models is to compute the estimated residual errors using Table 3.11.1 of Section 3.11. If this number is too large, then further testing in that test phase can be recommended. If the residual error estimate is small, then the CU may proceed to the next test phase (of course, the CU should not proceed to the next test phase until all the observed errors have been removed).

In conclusion, we feel that there is substantial evidence, both from this study, and from the study of Nagel and

Skrivan (1982) to discount the general applicability to C^3I projects of the software reliability models studied herein, and we strongly urge that none of them be adopted in any way as industry or government standards for C^3I projects like JSS. Moreover, we view these models as inappropriate for use by software acquisition managers in monitoring project status and the results of qualification testing.

5.3 Recommendations

While we cannot recommend the software reliability models studied in this report for general use, there are some alternative modeling techniques which are potentially useful for software error data. These techniques are well-established and heavily used in all aspects of engineering. A compelling advantage to these techniques is that mathematical software has been developed for them in most major scientific subroutine packages. These techniques are those of regression analysis, and time-series analysis.

Of course, before these techniques can be used, it must be decided what quantities are of interest. Clearly, no relatively simple mathematical model can encompass all the information concerning the effectiveness of software qualification testing. The acquisition manager must become actively involved in evaluating the testing techniques used to ensure that they are up to date and qualitatively adequate for the purposes of the software project under consideration. Having done this, the acquisition manager must decide which measureable attributes of qualification testing are important to monitor and predict. This is the point at which regression and/or time-series analysis can be possibly successfully applied.

For example, suppose that the cumulative number of errors detected during testing, and the cumulative number of errors removed are to be monitored. It is not difficult to select a regression function which will follow the shape of a typical plot of cumulative errors removed or detected versus time (calendar time) as seen in Figures 3.9.1 through 3.9.12 of Section 3.9. The fitting of such regression functions can provide short-run predictions of errors detected or removed, or of the point at which errors removed will equal errors detected, for example. After sufficient time has elapsed, an estimate for the total initial errors can be obtained if the regression function has a mathematical asymptote representing this value.

A more appropriate technique if predictions are required would be that of the time-series approach. While this technique cannot be fully described here, suffice it to say that the approach aims at identifying the underlying stochastic structure which relates successive observations, estimating any unknown parameters, and using the stochastic structure to make predictions for the future. The amount of time into the future for

which meaningful predictions can be made depends on the complexity of the underlying stochastic structure (see Box & Jenkins, 1970).

If stochastic models are needed for monitoring the number of software errors detected or removed, then these approaches (i.e. regression and time-series) are certainly worth looking into. Other quantitative methods may also provide aid to the acquisition manager such as the use of software quality metrics. More research is needed, however, to determine what relationship, if any, exists between software quality metrics and software reliability.

There is another important recommendation concerning quantitative software reliability modeling. In past attempts the same models proposed have been assumed to model software failures during all phases of the software's development and operation. There is convincing evidence, both from the results of this study and from common sense, that the detection of errors is test phase dependent. In fact, during testing, the detection of software errors may well be just as much a function of factors extraneous to the software (e.g. manpower, scheduling, test phase, testing intensity, programmer experience) as of the software itself. Thus, we recommend a dichotomy in future modeling attempts; one model or technique for monitoring quantities of interest during testing, and a different model or technique for application during mission operations. We further recommend that any future modeling studies be based on a thorough analysis of the causes and characteristics of software errors (during both testing and mission operations) rather than an unmotivated (except by mathematical convenience) set of assumptions. At the very least, any new models should be consistent with the empirical evidence collected thus far. For example Goel (1983), recognizing that empirically the cumulative error detected curve changes inflection and is not concave downward everywhere proposed a Nonhomogeneous Poisson model with a new mean value function of the form $a\{1-\exp(-bt^{c})\}$, $a>0, b>0, c>0$. This is a step in the right direction. Also, the proportional hazards model studied in Nagel and Skrivan (1982) is a good candidate for further study as a model appropriate for the development phase since it allows the inclusion of "covariates" which could include manpower, test phase, intensity of testing, etc.

Concerning the models investigated in this study, there is much more work to be done in the area of parameter estimation if these models are to receive any further serious consideration. Such problems as estimation techniques, starting points for iterative procedures, and uniqueness of estimators must be addressed.

Several follow-up studies can be recommended. First, the experiment done by Nagel & Skrivan (1982) should be repeated. At the very least, their data should be analyzed using different

techniques in order to strengthen their conclusions, or provide incentive to perform another similar experiment. Secondly, the JSS software error data collection should continue in order to obtain more operational data. This will facilitate future analysis of the data for both software reliability models and software metrics. Finally, other software projects (on the scale of JSS) should be studied to determine if the conclusions of this study will hold true, and if they are peculiar to the JSS project only.

The final recommendation concerns software standardization. Much of the success in hardware reliability modeling is due to the fact that so many electronic parts are standard. It is believed that in modern C^3I software, many functions (modules, perhaps) can also be standardized. Of course, there has not been (until the introduction of Ada) an acceptable industry standard programming language, which would be a natural prerequisite to standardization. It is believed by many software experts that standardized software could lead to a quantum improvement in software quality/reliability. Hughes-Fullerton is currently involved in software standardization studies (e.g. see Cooper, 1981; Andrulaitis, 1981), and this area certainly deserves further research.

APPENDIX A

Detailed Results of Modeling Fitting Attempts

This appendix contains the detailed results of the software reliability model fitting attempts. Each dataset is specified by CPCI, CU, and test phase (e.g. APS APC IT). For each dataset, each of the seven models are applied: Geometric Poisson (modified), Jelinski-Moranda, Nonhomogeneous Poisson, Generalized Poisson, IBM Poisson (modified), Binomial, and the IBM Poisson with Variable Alpha (original IBM Poisson). The output for a model consists of the model name, its parameter estimates and the number of iterations required in the iterative algorithms, the time interval lengths, observed number of errors, expected number of errors (estimated), the standard deviation (estimated) of the number of errors, the observed chi-square value, and the 0.95 quantile of the chi-square distribution with appropriate degrees of freedom. Sometimes an output is bypassed. These are cases where convergence failed and parameter estimates were not obtained. Also, sometimes a dataset is bypassed. These are datasets with insufficient data, i.e. datasets for which there were not enough time intervals in which no errors were removed.

APS APC IT

GEOMETRIC POISSON

THE ESTIMATE OF K=0.994421D+00
NUMBER OF ITERATIONS= 5

THE ESTIMATE OF LAMBDA=0.421118D+00

TAU	OBS	EXPECTED(COND)	SD(COND)
7.00	2	2.90	1.70
21.00	4	8.05	2.84
8.00	0	2.82	1.68
2.00	0	0.69	0.83
3.00	3	1.02	1.01
4.00	2	1.33	1.15
6.00	11	1.94	1.39
1.00	3	0.32	0.56
2.00	0	0.63	0.79
1.00	1	0.31	0.56
3.00	1	0.92	0.96
2.00	1	0.61	0.78
2.00	1	0.60	0.77
3.00	0	0.89	0.94
6.00	1	1.73	1.32
23.00	1	6.13	2.48
4.00	2	0.99	0.99
9.00	1	2.14	1.46

CHI-SQUARE=0.849987D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 16 DEGREES OF FREEDOM= 26.3011

JELINSKI-MORANDA

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= 75
THE ESTIMATE OF B= 0.5595D-02
NUMBER OF ITERATIONS= 1

TAU	OBS	EXPECTED(COND)	SD(COND)
7.00	2	2.90	1.70
21.00	4	8.05	2.84
8.00	0	2.82	1.68
2.00	0	0.69	0.83
3.00	3	1.02	1.01
4.00	2	1.33	1.15
6.00	11	1.94	1.39
1.00	3	0.32	0.56
2.00	0	0.63	0.79

1.00	1	0.31	0.56
3.00	1	0.92	0.96
2.00	1	0.61	0.78
2.00	1	0.60	0.77
3.00	0	0.89	0.94
6.00	1	1.73	1.32
23.00	1	6.13	2.48
4.00	2	0.99	0.99
9.00	1	2.14	1.46

CHI-SQUARE= 84.9987
0.950 QUANTILE FOR CHI-SQUARE WITH 16 DEGREES OF FREEDOM= 26.3011

GENERALIZED POISSON

IBM POISSON

THE ESTIMATE OF PHI=0.289329D-04
NUMBER OF ITERATIONS= 6

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS= 4355

TAU	OBS	EXPECTED(COND)	SD(COND)
7.00	2	2.23	1.49
21.00	4	6.70	2.59
8.00	0	2.55	1.60
2.00	0	0.64	0.80
3.00	3	0.96	0.98
4.00	2	1.27	1.13
6.00	11	1.91	1.38
1.00	3	0.32	0.56
2.00	0	0.64	0.80
1.00	1	0.32	0.56
3.00	1	0.95	0.98
2.00	1	0.63	0.80
2.00	1	0.63	0.80
3.00	0	0.95	0.98
6.00	1	1.90	1.38
23.00	1	7.28	2.70
4.00	2	1.27	1.13
9.00	1	2.85	1.69

CHI-SQUARE=0.858949D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 16 DEGREES OF FREEDOM= 26.3011

BINOMIAL

THE ESTIMATE OF N= 11
THE ESTIMATE OF A= 0.3122D-11

TAU	OBS	EXPECTED(COND)	SD(COND)

7.00	2	0.00	0.00
21.00	4	0.00	0.00
8.00	0	0.00	0.00
2.00	0	0.00	0.00
3.00	3	0.00	0.00
4.00	2	0.00	0.00
6.00	11	0.00	0.00
1.00	3	-0.00	0.00
2.00	0	-0.00	0.00
1.00	1	-0.00	0.00
3.00	1	-0.00	0.00
2.00	1	-0.00	0.00
2.00	1	-0.00	0.00
3.00	0	-0.00	0.00
6.00	1	-0.00	0.00
23.00	1	-0.00	0.00
4.00	2	-0.00	0.00
9.00	1	-0.00	0.00

CHI-SQUARE=**********
0.950 QUANTILE FOR CHI-SQUARE WITH 16 DEGREES OF FREEDOM= 26.3011

IBM POISSON WITH VARIABLE ALPHA

APS APC SD
APS APC ST

GEOMETRIC POISSON

THE ESTIMATE OF K=0.841352D+00
NUMBER OF ITERATIONS= 4

THE ESTIMATE OF LAMBDA=0.253984D+01

TAU	OBS	EXPECTED(COND)	SD(COND)
3.00	4	6.47	2.54
4.00	8	4.76	2.18
1.00	1	0.76	0.87
4.00	2	2.01	1.42
4.00	0	1.00	1.00

CHI-SQUARE=0.423891D+01
0.950 QUANTILE FOR CHI-SQUARE WITH 3 DEGREES OF FREEDOM= 7.8167

JELINSKI-MORANDA

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= 16
THE ESTIMATE OF B= 0.1727D+00
NUMBER OF ITERATIONS= 3

TAU	OBS	EXPECTED(COND)	SD(COND)
3.00	4	6.47	2.54
4.00	8	4.76	2.18
1.00	1	0.76	0.87
4.00	2	2.01	1.42
4.00	0	1.00	1.00

CHI-SQUARE= 4.2389
0.950 QUANTILE FOR CHI-SQUARE WITH 3 DEGREES OF FREEDOM= 7.8167

GENERALIZED POISSON

IBM POISSON

THE ESTIMATE OF PHI=-.138097D+00
NUMBER OF ITERATIONS= 11

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS= 3

TAU	OBS	EXPECTED(COND)	SD(COND)
3.00	4	-1.32	1.15
4.00	8	1.50	1.23
1.00	1	0.58	0.76
4.00	2	5.57	2.36
4.00	0	8.28	2.88

CHI-SQUARE=0.174588D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 3 DEGREES OF FREEDOM= 7.8167

BINOMIAL

THE ESTIMATE OF N= 17
THE ESTIMATE OF A= 0.1417D+00

TAU	OBS	EXPECTED(COND)	SD(COND)
3.00	4	5.97	2.44
4.00	8	5.72	2.39
1.00	1	0.69	0.83
4.00	2	1.83	1.35
4.00	0	0.97	0.98

CHI-SQUARE= 2.6718
0.950 QUANTILE FOR CHI-SQUARE WITH 3 DEGREES OF FREEDOM= 7.8147

IBM POISSON WITH VARIABLE ALPHA

APS APC IN

GEOMETRIC POISSON

THE ESTIMATE OF K=0.965733D+00
NUMBER OF ITERATIONS= 5

THE ESTIMATE OF LAMBDA=0.168276D+01

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	2	1.68	1.30
1.00	1	1.63	1.27
6.00	9	8.65	2.94
2.00	1	2.50	1.58
2.00	4	2.33	1.53
1.00	3	1.11	1.05
2.00	0	2.10	1.45

CHI-SQUARE=0.774280D+01
0.950 QUANTILE FOR CHI-SQUARE WITH 5 DEGREES OF FREEDOM= 11.0733

JELINSKI-MORANDA

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= 49
THE ESTIMATE OF B= 0.3487D-01
NUMBER OF ITERATIONS= 2

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	2	1.68	1.30
1.00	1	1.63	1.27
6.00	9	8.65	2.94
2.00	1	2.50	1.58
2.00	4	2.33	1.53
1.00	3	1.11	1.05
2.00	0	2.10	1.45

CHI-SQUARE= 7.7428
0.950 QUANTILE FOR CHI-SQUARE WITH 5 DEGREES OF FREEDOM= 11.0733

GENERALIZED POISSON

THE ESTIMATE OF N= 21
THE ESTIMATE OF ALPHA= 0.7964D+00
THE ESTIMATE OF PHI= 0.1338D+00
NUMBER OF ITERATIONS= 13

TAU	OBS	EXPECTED(COND)	SD(COND)

1.00	2	2.75	1.66
1.00	1	2.62	1.62
6.00	9	9.25	3.04
2.00	1	2.23	1.49
2.00	4	2.00	1.41
1.00	3	1.02	1.01
2.00	0	0.14	0.37

THE CUMULATIVE NUMBER OF ERRORS OBSERVED=0.200000D+02

CHI-SQUARE= 7.9205
0.950 QUANTILE FOR CHI-SQUARE WITH 4 DEGREES OF FREEDOM= 9.4917

IBM POISSON

THE ESTIMATE OF PHI=0.399117D-04
NUMBER OF ITERATIONS= 10

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS= 16399

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	2	1.33	1.16
1.00	1	1.33	1.16
6.00	9	8.00	2.83
2.00	1	2.67	1.63
2.00	4	2.67	1.63
1.00	3	1.33	1.15
2.00	0	2.66	1.63

CHI-SQUARE=0.699861D+01
0.950 QUANTILE FOR CHI-SQUARE WITH 5 DEGREES OF FREEDOM= 11.0733

BINOMIAL

THE ESTIMATE OF N= 5
THE ESTIMATE OF A=-0.2252D-13

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	2	-0.00	0.00
1.00	1	-0.00	0.00
6.00	9	-0.00	0.00
2.00	1	0.00	0.00
2.00	4	0.00	0.00
1.00	3	0.00	0.00
2.00	0	0.00	0.00

CHI-SQUARE=**********
0.950 QUANTILE FOR CHI-SQUARE WITH 5 DEGREES OF FREEDOM= 11.0733

IBM POISSON WITH VARIABLE ALPHA

APS ZEZ IT

GEOMETRIC POISSON

THE ESTIMATE OF K=0.102747D+01
NUMBER OF ITERATIONS= 6

THE ESTIMATE OF LAMBDA=0.276914D-01

TAU	OBS	EXPECTED(COND)	SD(COND)
56.00	0	3.59	1.89
18.00	1	2.89	1.70
13.00	12	3.16	1.78
2.00	3	0.59	0.77
1.00	3	0.31	0.56
3.00	1	0.98	0.99
2.00	1	0.70	0.84
4.00	1	1.51	1.23
18.00	1	9.27	3.04

CHI-SQUARE=0.704354D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 7 DEGREES OF FREEDOM= 14.0702

JELINSKI-MORANDA

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= 0
THE ESTIMATE OF B=-0.2710D-01
NUMBER OF ITERATIONS= 3

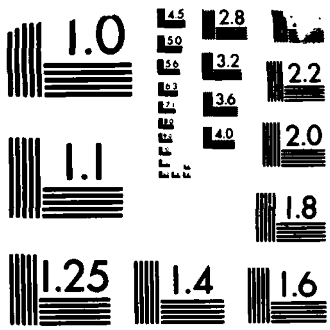
TAU	OBS	EXPECTED(COND)	SD(COND)
56.00	0	3.59	1.89
18.00	1	2.89	1.70
13.00	12	3.16	1.78
2.00	3	0.59	0.77
1.00	3	0.31	0.56
3.00	1	0.98	0.99
2.00	1	0.70	0.84
4.00	1	1.51	1.23
18.00	1	9.27	3.04

CHI-SQUARE= 70.4354
0.950 QUANTILE FOR CHI-SQUARE WITH 7 DEGREES OF FREEDOM= 14.0702

GENERALIZED POISSON

THE ESTIMATE OF N= 28

AD-A138 196 RELIABILITY MODEL DEMONSTRATION STUDY VOLUME 1(U) 3/4
HUGHES AIRCRAFT CO FULLERTON CA GROUND SYSTEMS GROUP
J E ANGUS ET AL. AUG 83 RADC-TR-83-207-VOL-1
UNCLASSIFIED F30602-80-C-0273 F/G 9/2 NL



MICROCOPY RESOLUTION TEST CHART
NATIONAL BUREAU OF STANDARDS-1963-A

THE ESTIMATE OF ALPHA=-0.1443D+00
THE ESTIMATE OF PHI= 0.2072D+00
NUMBER OF ITERATIONS= 7

TAU	OBS	EXPECTED(COND)	SD(COND)
56.00	0	3.21	1.79
18.00	1	3.64	1.91
13.00	12	3.68	1.92
2.00	3	4.63	2.15
1.00	3	3.46	1.86
3.00	1	1.53	1.24
2.00	1	1.25	1.12
4.00	1	0.96	0.98
18.00	1	0.64	0.80

THE CUMULATIVE NUMBER OF ERRORS OBSERVED=0.230000D+02

CHI-SQUARE= 25.0589
0.950 QUANTILE FOR CHI-SQUARE WITH 6 DEGREES OF FREEDOM= 12.5961

IBM POISSON

THE ESTIMATE OF PHI=0.815875D-02
NUMBER OF ITERATIONS= 5

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS= 37

TAU	OBS	EXPECTED(COND)	SD(COND)
56.00	0	13.51	3.68
18.00	1	4.90	2.21
13.00	12	3.51	1.87
2.00	3	0.55	0.74
1.00	3	0.21	0.46
3.00	1	0.43	0.66
2.00	1	0.26	0.51
4.00	1	0.47	0.69
18.00	1	1.88	1.37

CHI-SQUARE=0.891829D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 7 DEGREES OF FREEDOM= 14.0702

BINOMIAL

THE ESTIMATE OF N= 4
THE ESTIMATE OF A=-0.2118D-12

TAU	OBS	EXPECTED(COND)	SD(COND)
56.00	0	-0.00	0.00
18.00	1	-0.00	0.00

13.00	12	-0.00	0.00
2.00	3	0.00	0.00
1.00	3	0.00	0.00
3.00	1	0.00	0.00
2.00	1	0.00	0.00
4.00	1	0.00	0.00
18.00	1	0.00	0.00

CHI-SQUARE=**********
0.950 QUANTILE FOR CHI-SQUARE WITH 7 DEGREES OF FREEDOM= 14.0702

IBM POISSON WITH VARIABLE ALPHA

APS ZEZ SD

GEOMETRIC POISSON

THE ESTIMATE OF K=0.979595D+00
NUMBER OF ITERATIONS= 5

THE ESTIMATE OF LAMBDA=0.315432D+01

TAU	OBS	EXPECTED(COND)	SD(COND)
3.00	0	9.27	3.04
6.00	19	16.91	4.11
1.00	1	2.62	1.62
1.00	2	2.57	1.60
2.00	5	4.98	2.23
1.00	4	2.41	1.55
3.00	20	6.95	2.64
1.00	8	2.22	1.49
1.00	1	2.18	1.48
3.00	9	6.27	2.50
2.00	0	3.97	1.99
2.00	3	3.81	1.95
2.00	1	3.65	1.91
3.00	0	5.21	2.28

CHI-SQUARE=0.643555D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 12 DEGREES OF FREEDOM= 21.0297

JELINSKI-MORANDA

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= 155
THE ESTIMATE OF B= 0.2062D-01
NUMBER OF ITERATIONS= 2

TAU	OBS	EXPECTED(COND)	SD(COND)

3.00	0	9.27	3.04
6.00	19	16.91	4.11
1.00	1	2.62	1.62
1.00	2	2.57	1.60
2.00	5	4.98	2.23
1.00	4	2.41	1.55
3.00	20	6.95	2.64
1.00	8	2.22	1.49
1.00	1	2.18	1.48
3.00	9	6.27	2.50
2.00	0	3.97	1.99
2.00	3	3.81	1.95
2.00	1	3.65	1.91
3.00	0	5.21	2.28

CHI-SQUARE= 64.3555
0.950 QUANTILE FOR CHI-SQUARE WITH 12 DEGREES OF FREEDOM= 21.0297

GENERALIZED POISSON

APS ZEZ ST

GEOMETRIC POISSON

THE ESTIMATE OF K=0.930237D+00
NUMBER OF ITERATIONS= 4

THE ESTIMATE OF LAMBDA=0.203251D+01

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	0	2.03	1.43
3.00	3	5.29	2.30
2.00	5	2.94	1.71
3.00	8	3.68	1.92
1.00	1	1.06	1.03
8.00	5	6.21	2.49
4.00	2	1.99	1.41
1.00	0	0.41	0.64
4.00	1	1.39	1.18

CHI-SQUARE=0.102941D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 7 DEGREES OF FREEDOM= 14.0702

JELINSKI-MORANDA

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= 29
THE ESTIMATE OF B= 0.7232D-01
NUMBER OF ITERATIONS= 2

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	0	2.03	1.43
3.00	3	5.29	2.30
2.00	5	2.94	1.71
3.00	8	3.68	1.92
1.00	1	1.06	1.03
8.00	5	6.21	2.49
4.00	2	1.99	1.41
1.00	0	0.41	0.64
4.00	1	1.39	1.18

CHI-SQUARE= 10.2941
0.950 QUANTILE FOR CHI-SQUARE WITH 7 DEGREES OF FREEDOM= 14.0702

GENERALIZED POISSON

THE ESTIMATE OF N= 27
THE ESTIMATE OF ALPHA= 0.1180D+01
THE ESTIMATE OF PHI= 0.6065D-01
NUMBER OF ITERATIONS= 7

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	0	1.64	1.28
3.00	3	5.77	2.40
2.00	5	3.44	1.85
3.00	8	4.22	2.05
1.00	1	0.79	0.89
8.00	5	6.37	2.52
4.00	2	1.57	1.25
1.00	0	0.25	0.50
4.00	1	0.95	0.97

THE CUMULATIVE NUMBER OF ERRORS OBSERVED=0.250000D+02

CHI-SQUARE= 7.7806
0.950 QUANTILE FOR CHI-SQUARE WITH 6 DEGREES OF FREEDOM= 12.5961

IBM POISSON

THE ESTIMATE OF PHI=0.723783D-01
NUMBER OF ITERATIONS= 4

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS= 29

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	0	2.08	1.44
3.00	3	5.59	2.36
2.00	5	3.72	1.93
3.00	8	4.17	2.04
1.00	1	1.06	1.03

8.00	5	4.83	2.20
4.00	2	1.74	1.32
1.00	0	0.41	0.64
4.00	1	1.22	1.10

CHI-SQUARE=0.771846D+01
0.950 QUANTILE FOR CHI-SQUARE WITH 7 DEGREES OF FREEDOM= 14.0702

BINOMIAL

THE ESTIMATE OF N= 30
THE ESTIMATE OF A= 0.6891D-01

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	0	1.99	1.41
3.00	3	5.59	2.36
2.00	5	3.47	1.86
3.00	8	4.10	2.02
1.00	1	0.93	0.96
8.00	5	5.48	2.34
4.00	2	1.91	1.38
1.00	0	0.40	0.63
4.00	1	1.43	1.20

CHI-SQUARE= 8.1655
0.950 QUANTILE FOR CHI-SQUARE WITH 7 DEGREES OF FREEDOM= 14.0702

IBM POISSON WITH VARIABLE ALPHA

APS ZEZ IN

GEOMETRIC POISSON

THE ESTIMATE OF K=0.834404D+00
NUMBER OF ITERATIONS= 4

THE ESTIMATE OF LAMBDA=0.159596D+01

TAU	OBS	EXPECTED(COND)	SD(COND)
3.00	5	4.04	2.01
2.00	0	1.70	1.30
2.00	1	1.18	1.09
5.00	3	1.62	1.27
3.00	0	0.46	0.68

CHI-SQUARE=0.360281D+01
0.950 QUANTILE FOR CHI-SQUARE WITH 3 DEGREES OF FREEDOM= 7.8167

JELINSKI-MORANDA

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= 10
THE ESTIMATE OF B= 0.1810D+00
NUMBER OF ITERATIONS= 3

TAU	OBS	EXPECTED(COND)	SD(COND)
3.00	5	4.04	2.01
2.00	0	1.70	1.30
2.00	1	1.18	1.09
5.00	3	1.62	1.27
3.00	0	0.46	0.68

CHI-SQUARE= 3.6028
0.950 QUANTILE FOR CHI-SQUARE WITH 3 DEGREES OF FREEDOM= 7.8167

GENERALIZED POISSON

IBM POISSON

THE ESTIMATE OF PHI=0.178307D+00
NUMBER OF ITERATIONS= 5

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS= 8

TAU	OBS	EXPECTED(COND)	SD(COND)
3.00	5	3.65	1.91
2.00	0	2.01	1.42
2.00	1	1.69	1.30
5.00	3	1.38	1.17
3.00	0	-0.36	0.60

CHI-SQUARE=0.435399D+01
0.950 QUANTILE FOR CHI-SQUARE WITH 3 DEGREES OF FREEDOM= 7.8167

BINOMIAL

THE ESTIMATE OF N= 9
THE ESTIMATE OF A= 0.2249D+00

TAU	OBS	EXPECTED(COND)	SD(COND)
3.00	5	4.52	2.13
2.00	0	1.53	1.24
2.00	1	1.53	1.24
5.00	3	2.17	1.47
3.00	0	0.10	0.32

CHI-SQUARE= 2.1812
0.950 QUANTILE FOR CHI-SQUARE WITH 3 DEGREES OF FREEDOM= 7.8167

IBM POISSON WITH VARIABLE ALPHA

APS ASZ IT

GEOMETRIC POISSON

THE ESTIMATE OF K=0.102471D+01
NUMBER OF ITERATIONS= 6

THE ESTIMATE OF LAMBDA=0.100455D+00

TAU	OBS	EXPECTED(COND)	SD(COND)
54.00	3	11.12	3.34
2.00	0	0.76	0.87
4.00	0	1.64	1.28
5.00	2	2.28	1.51
2.00	1	0.99	1.00
1.00	0	0.52	0.72
1.00	2	0.53	0.73
1.00	2	0.54	0.74
3.00	10	1.71	1.31
1.00	3	0.60	0.77
1.00	1	0.61	0.78
5.00	12	3.29	1.81
2.00	3	1.43	1.20
1.00	1	0.74	0.86
2.00	1	1.54	1.24
2.00	2	1.62	1.27
2.00	2	1.70	1.30
2.00	0	1.79	1.34
3.00	2	2.85	1.69
3.00	3	3.06	1.75
1.00	2	1.07	1.04
1.00	1	1.10	1.05
1.00	1	1.13	1.06
6.00	2	7.36	2.71
5.00	1	7.02	2.65

CHI-SQUARE=0.104274D+03
0.950 QUANTILE FOR CHI-SQUARE WITH 23 DEGREES OF FREEDOM= 35.1779

JELINSKI-MORANDA

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= -3
THE ESTIMATE OF B=-0.2441D-01
NUMBER OF ITERATIONS= 3

TAU	OBS	EXPECTED(COND)	SD(COND)
54.00	3	11.12	3.34
2.00	0	0.76	0.87
4.00	0	1.64	1.28
5.00	2	2.28	1.51
2.00	1	0.99	1.00
1.00	0	0.52	0.72
1.00	2	0.53	0.73
1.00	2	0.54	0.74
3.00	10	1.71	1.31
1.00	3	0.60	0.77
1.00	1	0.61	0.78
5.00	12	3.29	1.81
2.00	3	1.43	1.20
1.00	1	0.74	0.86
2.00	1	1.54	1.24
2.00	2	1.62	1.27
2.00	2	1.70	1.30
2.00	0	1.79	1.34
3.00	2	2.85	1.69
3.00	3	3.06	1.75
1.00	2	1.07	1.04
1.00	1	1.10	1.05
1.00	1	1.13	1.06
6.00	2	7.36	2.71
5.00	1	7.02	2.65

CHI-SQUARE= 104.2743
0.950 QUANTILE FOR CHI-SQUARE WITH 23 DEGREES OF FREEDOM= 35.1779

GENERALIZED POISSON

THE ESTIMATE OF N= 258
THE ESTIMATE OF ALPHA= 0.2672D+00
THE ESTIMATE OF PHI= 0.7691D-02
NUMBER OF ITERATIONS= 12

TAU	OBS	EXPECTED(COND)	SD(COND)
54.00	3	5.75	2.40
2.00	0	2.38	1.54
4.00	0	2.85	1.69
5.00	2	3.01	1.74
2.00	1	2.35	1.53
1.00	0	1.94	1.39
1.00	2	1.94	1.39
1.00	2	1.93	1.39
3.00	10	2.54	1.60
1.00	3	1.87	1.37
1.00	1	1.83	1.35
5.00	12	2.77	1.67
2.00	3	2.09	1.45
1.00	1	1.71	1.31
2.00	1	2.02	1.42
2.00	2	2.01	1.42

2.00	2	2.00	1.41
2.00	0	1.99	1.41
3.00	2	2.18	1.48
3.00	3	2.16	1.47
1.00	2	1.60	1.27
1.00	1	1.59	1.26
1.00	1	1.58	1.26
6.00	2	2.52	1.59
5.00	1	2.38	1.54

THE CUMULATIVE NUMBER OF ERRORS OBSERVED=0.570000D+02

CHI-SQUARE= 68.1667
0.950 QUANTILE FOR CHI-SQUARE WITH 22 DEGREES OF FREEDOM= 33.9327

IBM POISSON

THE ESTIMATE OF PHI=0.298916D-04
NUMBER OF ITERATIONS= 10

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS= 8996

TAU	OBS	EXPECTED(COND)	SD(COND)
54.00	3	27.77	5.27
2.00	0	1.03	1.01
4.00	0	2.06	1.44
5.00	2	2.57	1.60
2.00	1	1.03	1.01
1.00	0	0.51	0.72
1.00	2	0.51	0.72
1.00	2	0.51	0.72
3.00	10	1.54	1.24
1.00	3	0.51	0.72
1.00	1	0.51	0.72
5.00	12	2.57	1.60
2.00	3	1.03	1.01
1.00	1	0.51	0.72
2.00	1	1.03	1.01
2.00	2	1.03	1.01
2.00	2	1.03	1.01
2.00	0	1.03	1.01
3.00	2	1.54	1.24
3.00	3	1.54	1.24
1.00	2	0.51	0.72
1.00	1	0.51	0.72
1.00	1	0.51	0.72
6.00	2	3.07	1.75
5.00	1	2.56	1.60

CHI-SQUARE=0.143081D+03
0.950 QUANTILE FOR CHI-SQUARE WITH 23 DEGREES OF FREEDOM= 35.1779

BINOMIAL

THE ESTIMATE OF N=   14
THE ESTIMATE OF A= 0.2189D-11

TAU	OBS	EXPECTED(COND)	SD(COND)
54.00	3	0.00	0.00
2.00	0	0.00	0.00
4.00	0	0.00	0.00
5.00	2	0.00	0.00
2.00	1	0.00	0.00
1.00	0	0.00	0.00
1.00	2	0.00	0.00
1.00	2	0.00	0.00
3.00	10	0.00	0.00
1.00	3	-0.00	0.00
1.00	1	-0.00	0.00
5.00	12	-0.00	0.00
2.00	3	-0.00	0.00
1.00	1	-0.00	0.00
2.00	1	-0.00	0.00
2.00	2	-0.00	0.00
2.00	2	-0.00	0.00
2.00	0	-0.00	0.00
3.00	2	-0.00	0.00
3.00	3	-0.00	0.00
1.00	2	-0.00	0.00
1.00	1	-0.00	0.00
1.00	1	-0.00	0.00
6.00	2	-0.00	0.00
5.00	1	-0.00	0.00

CHI-SQUARE=**********
0.950 QUANTILE FOR CHI-SQUARE WITH 23 DEGREES OF FREEDOM=   35.1779

IBM POISSON WITH VARIABLE ALPHA

APS ASZ SD

GEOMETRIC POISSON

THE ESTIMATE OF K=0.932464D+00
NUMBER OF ITERATIONS= 5

THE ESTIMATE OF LAMBDA=0.146270D+01

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	1	1.46	1.21
3.00	3	3.82	1.95
2.00	5	2.14	1.46
1.00	0	0.96	0.98
2.00	2	1.73	1.32
4.00	2	2.82	1.68
2.00	1	1.14	1.07
3.00	2	1.44	1.20

3.00	0	1.16	1.08
5.00	2	1.47	1.21
4.00	1	0.86	0.93

CHI-SQUARE=0.701424D+01
0.950 QUANTILE FOR CHI-SQUARE WITH 9 DEGREES OF FREEDOM= 16.9252

JELINSKI-MORANDA

THE ESTIMATE OF N= 22
THE ESTIMATE OF ALPHA= 0.1000D+01
THE ESTIMATE OF PHI= 0.5726D-01
NUMBER OF ITERATIONS= 10

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	1	1.28	1.13
3.00	3	3.67	1.92
2.00	5	2.33	1.53
1.00	0	0.99	1.00
2.00	2	1.76	1.33
4.00	2	2.60	1.61
2.00	1	1.19	1.09
3.00	2	1.61	1.27
3.00	0	1.26	1.12
5.00	2	1.53	1.24
4.00	1	0.77	0.88

CHI-SQUARE= 6.0026
0.950 QUANTILE FOR CHI-SQUARE WITH 9 DEGREES OF FREEDOM= 16.9252

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= 22
THE ESTIMATE OF B= 0.6992D-01
NUMBER OF ITERATIONS= 2

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	1	1.46	1.21
3.00	3	3.82	1.95
2.00	5	2.14	1.46
1.00	0	0.96	0.98
2.00	2	1.73	1.32
4.00	2	2.82	1.68
2.00	1	1.14	1.07
3.00	2	1.44	1.20
3.00	0	1.16	1.08
5.00	2	1.47	1.21
4.00	1	0.86	0.93

CHI-SQUARE= 7.0142
0.950 QUANTILE FOR CHI-SQUARE WITH 9 DEGREES OF FREEDOM= 16.9252

GENERALIZED POISSON

THE ESTIMATE OF N= 22
THE ESTIMATE OF ALPHA= 0.1148D+01
THE ESTIMATE OF PHI= 0.5185D-01
NUMBER OF ITERATIONS= 6

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	1	1.14	1.07
3.00	3	3.83	1.96
2.00	5	2.29	1.51
1.00	0	0.88	0.94
2.00	2	1.71	1.31
4.00	2	2.78	1.67
2.00	1	1.14	1.07
3.00	2	1.63	1.28
3.00	0	1.26	1.12
5.00	2	1.61	1.27
4.00	1	0.74	0.86

THE CUMULATIVE NUMBER OF ERRORS OBSERVED=0.190000D+02

CHI-SQUARE= 6.1032
0.950 QUANTILE FOR CHI-SQUARE WITH 8 DEGREES OF FREEDOM= 15.5118

IBM POISSON

THE ESTIMATE OF PHI=0.585848D-01
NUMBER OF ITERATIONS= 5

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS= 23

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	1	1.33	1.15
3.00	3	3.59	1.90
2.00	5	2.35	1.53
1.00	0	1.04	1.02
2.00	2	1.78	1.34
4.00	2	2.51	1.58
2.00	1	1.22	1.10
3.00	2	1.61	1.27
3.00	0	1.27	1.13
5.00	2	1.48	1.22
4.00	1	0.79	0.89

CHI-SQUARE=0.596618D+01
0.950 QUANTILE FOR CHI-SQUARE WITH 9 DEGREES OF FREEDOM= 16.9252

BINOMIAL

THE ESTIMATE OF N= 21
THE ESTIMATE OF A= 0.7410D-01

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	1	1.51	1.23
3.00	3	4.03	2.01
2.00	5	2.37	1.54
1.00	0	0.87	0.93
2.00	2	1.68	1.30
4.00	2	2.62	1.62
2.00	1	1.13	1.06
3.00	2	1.43	1.20
3.00	0	1.04	1.02
5.00	2	1.61	1.27
4.00	1	0.82	0.91

CHI-SQUARE= 5.8426
0.950 QUANTILE FOR CHI-SQUARE WITH 9 DEGREES OF FREEDOM= 16.9252

IBM POISSON WITH VARIABLE ALPHA

APS ASZ ST

GEOMETRIC POISSON

THE ESTIMATE OF K=0.102117D+01
NUMBER OF ITERATIONS= 5

THE ESTIMATE OF LAMBDA=0.406796D+00

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	0	0.41	0.64
7.00	3	3.10	1.76
5.00	3	2.51	1.58
3.00	3	1.64	1.28
4.00	1	2.35	1.53

CHI-SQUARE=0.241613D+01
0.950 QUANTILE FOR CHI-SQUARE WITH 3 DEGREES OF FREEDOM= 7.8167

JELINSKI-MORANDA

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= -18
THE ESTIMATE OF B=-0.2095D-01
NUMBER OF ITERATIONS= 2

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	0	0.41	0.64
7.00	3	3.10	1.76
5.00	3	2.51	1.58
3.00	3	1.64	1.28
4.00	1	2.35	1.53

CHI-SQUARE= 2.4161
0.950 QUANTILE FOR CHI-SQUARE WITH 3 DEGREES OF FREEDOM= 7.8167

GENERALIZED POISSON

IBM POISSON

THE ESTIMATE OF PHI=0.508191D-04
NUMBER OF ITERATIONS= 10

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS= 5643

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	0	0.50	0.71
7.00	3	3.50	1.87
5.00	3	2.50	1.58
3.00	3	1.50	1.22
4.00	1	2.00	1.41

CHI-SQUARE=0.267247D+01
0.950 QUANTILE FOR CHI-SQUARE WITH 3 DEGREES OF FREEDOM= 7.8167

BINOMIAL

THE ESTIMATE OF N= 3
THE ESTIMATE OF A= 0.6326D-12

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	0	0.00	0.00
7.00	3	0.00	0.00
5.00	3	-0.00	0.00
3.00	3	-0.00	0.00
4.00	1	-0.00	0.00

CHI-SQUARE=**********
0.950 QUANTILE FOR CHI-SQUARE WITH 3 DEGREES OF FREEDOM= 7.8167

IBM POISSON WITH VARIABLE ALPHA

APS ASZ IN
APS ACZ IT

GEOMETRIC POISSON

THE ESTIMATE OF K=0.977949D+00
NUMBER OF ITERATIONS= 4

THE ESTIMATE OF LAMBDA=0.633254D+00

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	0	0.63	0.80
17.00	3	8.86	2.98
3.00	5	1.24	1.12
3.00	2	1.16	1.08
1.00	0	0.37	0.61
3.00	2	1.06	1.03
2.00	2	0.67	0.82
2.00	0	0.64	0.80
6.00	3	1.76	1.33
3.00	2	0.80	0.89
1.00	0	0.25	0.50
6.00	4	1.41	1.19
5.00	1	1.04	1.02
4.00	0	0.75	0.87
6.00	0	1.01	1.00
18.00	0	2.33	1.53

CHI-SQUARE=0.327169D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 14 DEGREES OF FREEDOM= 23.6908

JELINSKI-MORANDA

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= 29
THE ESTIMATE OF B= 0.2230D-01
NUMBER OF ITERATIONS= 2

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	0	0.63	0.80
17.00	3	8.86	2.98
3.00	5	1.24	1.12
3.00	2	1.16	1.08
1.00	0	0.37	0.61
3.00	2	1.06	1.03
2.00	2	0.67	0.82
2.00	0	0.64	0.80
6.00	3	1.76	1.33
3.00	2	0.80	0.89
1.00	0	0.25	0.50
6.00	4	1.41	1.19
5.00	1	1.04	1.02

4.00	0	0.75	0.87
6.00	0	1.01	1.00
18.00	0	2.33	1.53

CHI-SQUARE= 32.7169
0.950 QUANTILE FOR CHI-SQUARE WITH 14 DEGREES OF FREEDOM= 23.6908

GENERALIZED POISSON

THE ESTIMATE OF N= 20
THE ESTIMATE OF ALPHA= 0.61320+00
THE ESTIMATE OF PHI= 0.10200+00
NUMBER OF ITERATIONS= 7

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	0	2.01	1.42
17.00	3	10.86	3.30
3.00	5	3.35	1.83
3.00	2	3.15	1.77
1.00	0	1.50	1.23
3.00	2	2.35	1.53
2.00	2	1.21	1.10
2.00	0	1.05	1.02
6.00	3	1.75	1.32
3.00	2	0.55	0.74
1.00	0	0.18	0.42
6.00	4	0.22	0.47
5.00	1	-0.07	0.27
4.00	0	-0.54	0.74
6.00	0	-1.00	1.00
18.00	0	-2.56	1.60

THE CUMULATIVE NUMBER OF ERRORS OBSERVED=0.2400000+02

CHI-SQUARE= 60.9782
0.950 QUANTILE FOR CHI-SQUARE WITH 13 DEGREES OF FREEDOM= 22.3668

IBM POISSON

THE ESTIMATE OF PHI=-.4701820-04
NUMBER OF ITERATIONS= 9

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS= -3386

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	0	0.29	0.54
17.00	3	5.02	2.24
3.00	5	0.89	0.94
3.00	2	0.89	0.94
1.00	0	0.30	0.54
3.00	2	0.89	0.94

2.00	2	0.59	0.77
2.00	0	0.59	0.77
6.00	3	1.78	1.33
3.00	2	0.89	0.94
1.00	0	0.30	0.54
6.00	4	1.78	1.33
5.00	1	1.48	1.22
4.00	0	1.19	1.09
6.00	0	1.78	1.33
18.00	0	5.35	2.31

CHI-SQUARE=0.410310D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 14 DEGREES OF FREEDOM= 23.6908

BINOMIAL

IBM POISSON WITH VARIABLE ALPHA

APS ACZ SD
APS ACZ ST

GEOMETRIC POISSON

THE ESTIMATE OF K=0.103565D+01
NUMBER OF ITERATIONS= 6

THE ESTIMATE OF LAMBDA=0.191902D+00

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	0	0.19	0.44
7.00	1	1.55	1.24
6.00	2	1.67	1.29
3.00	2	0.97	0.99
4.00	2	1.47	1.21
5.00	1	2.15	1.47

CHI-SQUARE=0.234168D+01
0.950 QUANTILE FOR CHI-SQUARE WITH 4 DEGREES OF FREEDOM= 9.4917

JELINSKI-MORANDA

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= -4
THE ESTIMATE OF B=-0.3503D-01
NUMBER OF ITERATIONS= 3

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	0	0.19	0.44

7.00	1	1.55	1.24
6.00	2	1.67	1.29
3.00	2	0.97	0.99
4.00	2	1.47	1.21
5.00	1	2.15	1.47

CHI-SQUARE= 2.3417
0.950 QUANTILE FOR CHI-SQUARE WITH 4 DEGREES OF FREEDOM= 9.4917

GENERALIZED POISSON

IBM POISSON

THE ESTIMATE OF PHI=0.302269D-04
NUMBER OF ITERATIONS= 10

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS= 5476

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	0	0.31	0.55
7.00	1	2.15	1.47
6.00	2	1.85	1.36
3.00	2	0.92	0.96
4.00	2	1.23	1.11
5.00	1	1.54	1.24

CHI-SQUARE=0.286493D+01
0.950 QUANTILE FOR CHI-SQUARE WITH 4 DEGREES OF FREEDOM= 9.4917

BINOMIAL

THE ESTIMATE OF N= 3
THE ESTIMATE OF A=-0.2284D-14

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	0	-0.00	0.00
7.00	1	-0.00	0.00
6.00	2	-0.00	0.00
3.00	2	0.00	0.00
4.00	2	0.00	0.00
5.00	1	0.00	0.00

CHI-SQUARE=**********
0.950 QUANTILE FOR CHI-SQUARE WITH 4 DEGREES OF FREEDOM= 9.4917

IBM POISSON WITH VARIABLE ALPHA

APS ACZ IN
APS MMC IT

GEOMETRIC POISSON

THE ESTIMATE OF K=0.100530D+01
NUMBER OF ITERATIONS= 4

THE ESTIMATE OF LAMBDA=0.114699D+00

TAU	OBS	EXPECTED(COND)	SD(COND)
8.00	1	0.93	0.97
11.00	0	1.35	1.16
8.00	2	1.03	1.02
7.00	1	0.94	0.97
1.00	1	0.14	0.37
5.00	2	0.70	0.84
34.00	2	5.26	2.29
4.00	2	0.68	0.83
5.00	1	0.88	0.94
6.00	1	1.08	1.04

CHI-SQUARE=0.146996D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 8 DEGREES OF FREEDOM= 15.5118

JELINSKI-MORANDA

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= -21
THE ESTIMATE OF B=-0.5285D-02
NUMBER OF ITERATIONS= 3

TAU	OBS	EXPECTED(COND)	SD(COND)
8.00	1	0.93	0.97
11.00	0	1.35	1.16
8.00	2	1.03	1.02
7.00	1	0.94	0.97
1.00	1	0.14	0.37
5.00	2	0.70	0.84
34.00	2	5.26	2.29
4.00	2	0.68	0.83
5.00	1	0.88	0.94
6.00	1	1.08	1.04

CHI-SQUARE= 14.6996
0.950 QUANTILE FOR CHI-SQUARE WITH 8 DEGREES OF FREEDOM= 15.5118

GENERALIZED POISSON

IBM POISSON

THE ESTIMATE OF PHI=0.104102D-02
NUMBER OF ITERATIONS= 10

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS= 145

TAU	OBS	EXPECTED(COND)	SD(COND)
8.00	1	1.23	1.11
11.00	0	1.68	1.30
8.00	2	1.21	1.10
7.00	1	1.05	1.02
1.00	1	0.15	0.39
5.00	2	0.74	0.86
34.00	2	4.87	2.21
4.00	2	0.58	0.76
5.00	1	0.71	0.84
6.00	1	0.84	0.92

CHI-SQUARE=0.145921D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 8 DEGREES OF FREEDOM= 15.5118

BINOMIAL

IBM POISSON WITH VARIABLE ALPHA

APS MMC SD

GEOMETRIC POISSON

THE ESTIMATE OF K=0.925938D+00
NUMBER OF ITERATIONS= 4

THE ESTIMATE OF LAMBDA=0.395160D+00

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	1	0.40	0.63
4.00	0	1.31	1.14
5.00	2	1.16	1.08
6.00	1	0.91	0.96
2.00	0	0.22	0.47

CHI-SQUARE=0.307359D+01
0.950 QUANTILE FOR CHI-SQUARE WITH 3 DEGREES (F FREEDOM= 7.8167

JELINSKI-MORANDA

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= 5

THE ESTIMATE OF B= 0.7695D-01
NUMBER OF ITERATIONS= 2

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	1	0.40	0.63
4.00	0	1.31	1.14
5.00	2	1.16	1.08
6.00	1	0.91	0.96
2.00	0	0.22	0.47

CHI-SQUARE= 3.0736
0.950 QUANTILE FOR CHI-SQUARE WITH 3 DEGREES OF FREEDOM= 7.8167

GENERALIZED POISSON

IBM POISSON

THE ESTIMATE OF PHI=-.4154880D-04
NUMBER OF ITERATIONS= 14

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS= -2742

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	1	0.22	0.47
4.00	0	0.89	0.94
5.00	2	1.11	1.05
6.00	1	1.33	1.15
2.00	0	0.44	0.67

CHI-SQUARE=0.4854320+01
0.950 QUANTILE FOR CHI-SQUARE WITH 3 DEGREES OF FREEDOM= 7.8167

BINOMIAL

THE ESTIMATE OF N= 5
THE ESTIMATE OF A= 0.69890-01

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	1	0.37	0.61
4.00	0	1.09	1.05
5.00	2	1.32	1.15
6.00	1	0.85	0.92
2.00	0	0.19	0.44

CHI-SQUARE= 2.7291
0.950 QUANTILE FOR CHI-SQUARE WITH 3 DEGREES OF FREEDOM= 7.8167

IBM POISSON WITH VARIABLE ALPHA

APS MMC ST

GEOMETRIC POISSON

THE ESTIMATE OF K=0.922865D+00
NUMBER OF ITERATIONS= 4

THE ESTIMATE OF LAMBDA=0.131211D+01

TAU	OBS	EXPECTED(COND)	SD(COND)
3.00	2	3.64	1.91
4.00	6	3.67	1.92
5.00	3	3.21	1.79
6.00	2	2.48	1.58

CHI-SQUARE=0.232187D+01
0.950 QUANTILE FOR CHI-SQUARE WITH 2 DEGREES OF FREEDOM= 5.9948

JELINSKI-MORANDA

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= 17
THE ESTIMATE OF B= 0.8027D-01
NUMBER OF ITERATIONS= 2

TAU	OBS	EXPECTED(COND)	SD(COND)
3.00	2	3.64	1.91
4.00	6	3.67	1.92
5.00	3	3.21	1.79
6.00	2	2.48	1.58

CHI-SQUARE= 2.3219
0.950 QUANTILE FOR CHI-SQUARE WITH 2 DEGREES OF FREEDOM= 5.9948

GENERALIZED POISSON

IBM POISSON

THE ESTIMATE OF PHI=0.783457D-01
NUMBER OF ITERATIONS= 3

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS= 16

TAU	OBS	EXPECTED(COND)	SD(COND)

3.00	2	3.54	1.88
4.00	6	4.26	2.06
5.00	3	3.11	1.76
6.00	2	2.04	1.43

CHI-SQUARE=0.138674D+01
0.950 QUANTILE FOR CHI-SQUARE WITH 2 DEGREES OF FREEDOM= 5.9948

BINOMIAL

THE ESTIMATE OF N= 17
THE ESTIMATE OF A= 0.84680-01

TAU	OBS	EXPECTED(COND)	SD(COND)
3.00	2	3.75	1.94
4.00	6	4.23	2.06
5.00	3	3.01	1.74
6.00	2	2.28	1.51

CHI-SQUARE= 1.5927
0.950 QUANTILE FOR CHI-SQUARE WITH 2 DEGREES OF FREEDOM= 5.9948

IBM POISSON WITH VARIABLE ALPHA

APS MMC IN

GEOMETRIC POISSON

THE ESTIMATE OF K=0.987861D+00
NUMBER OF ITERATIONS= 5

THE ESTIMATE OF LAMBDA=0.188542D+01

TAU	OBS	EXPECTED(COND)	SD(COND)
5.00	8	9.20	3.03
1.00	2	1.77	1.33
4.00	9	6.88	2.62
4.00	6	6.55	2.56
1.00	1	1.59	1.26

CHI-SQUARE=0.110255D+01
0.950 QUANTILE FOR CHI-SQUARE WITH 3 DEGREES OF FREEDOM= 7.8167

JELINSKI-MORANDA

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= 155

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THE ESTIMATE OF B= 0.1221D-01
NUMBER OF ITERATIONS=     2
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TAU	OBS	EXPECTED(COND)	SD(COND)
5.00	8	9.20	3.03
1.00	2	1.77	1.33
4.00	9	6.88	2.62
4.00	6	6.55	2.56
1.00	1	1.59	1.26

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CHI-SQUARE=     1.1025
0.950 QUANTILE FOR CHI-SQUARE WITH   3 DEGREES OF FREEDOM=     7.8167
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GENERALIZED POISSON

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THE ESTIMATE OF N=     69
THE ESTIMATE OF ALPHA= 0.9792D+00
THE ESTIMATE OF PHI= 0.2873D-01
NUMBER OF ITERATIONS=     9
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TAU	OBS	EXPECTED(COND)	SD(COND)
5.00	8	9.62	3.10
1.00	2	1.96	1.40
4.00	9	7.17	2.68
4.00	6	5.95	2.44
1.00	1	1.30	1.14

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THE CUMULATIVE NUMBER OF ERRORS OBSERVED=0.260000D+02

CHI-SQUARE=     0.8083
0.950 QUANTILE FOR CHI-SQUARE WITH   2 DEGREES OF FREEDOM=     5.9948
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IBM POISSON

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THE ESTIMATE OF PHI=0.402554D-04
NUMBER OF ITERATIONS=   8

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS=  20401
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TAU	OBS	EXPECTED(COND)	SD(COND)
5.00	8	8.67	2.94
1.00	2	1.73	1.32
4.00	9	6.93	2.63
4.00	6	6.93	2.63
1.00	1	1.73	1.32

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CHI-SQUARE=0.114232D+01
0.950 QUANTILE FOR CHI-SQUARE WITH   3 DEGREES OF FREEDOM=     7.8167
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BINOMIAL

IBM POISSON WITH VARIABLE ALPHA

APS ATZ IT

GEOMETRIC POISSON

THE ESTIMATE OF K=0.100193D+01
NUMBER OF ITERATIONS= 4

THE ESTIMATE OF LAMBDA=0.178376D+00

TAU	OBS	EXPECTED(COND)	SD(COND)
28.00	4	5.13	2.26
14.00	3	2.67	1.63
1.00	0	0.19	0.44
4.00	2	0.78	0.88
2.00	0	0.39	0.63
5.00	1	0.98	0.99
3.00	2	0.60	0.77
1.00	1	0.20	0.45
2.00	1	0.40	0.63
18.00	1	3.66	1.91

CHI-SQUARE=0.121756D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 8 DEGREES OF FREEDOM= 15.5118

JELINSKI-MORANDA

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= -91
THE ESTIMATE OF B=-0.1929D-02
NUMBER OF ITERATIONS= 3

TAU	OBS	EXPECTED(COND)	SD(COND)
28.00	4	5.13	2.26
14.00	3	2.67	1.63
1.00	0	0.19	0.44

APS ATZ IT

GEOMETRIC POISSON

THE ESTIMATE OF K=0.100193D+01
NUMBER OF ITERATIONS= 4

THE ESTIMATE OF LAMBDA=0.178376D+00

TAU	OBS	EXPECTED(COND)	SD(COND)
28.00	4	5.13	2.26
14.00	3	2.67	1.63
1.00	0	0.19	0.44
4.00	2	0.78	0.88
2.00	0	0.39	0.63
5.00	1	0.98	0.99
3.00	2	0.60	0.77
1.00	1	0.20	0.45
2.00	1	0.40	0.63
18.00	1	3.66	1.91

CHI-SQUARE=0.121756D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 8 DEGREES OF FREEDOM= 15.5118

JELINSKI-MORANDA

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= -91
THE ESTIMATE OF B=-0.1929D-02
NUMBER OF ITERATIONS= 3

TAU	OBS	EXPECTED(COND)	SD(COND)
28.00	4	5.13	2.26
14.00	3	2.67	1.63
1.00	0	0.19	0.44
4.00	2	0.78	0.88
2.00	0	0.39	0.63
5.00	1	0.98	0.99
3.00	2	0.60	0.77
1.00	1	0.20	0.45
2.00	1	0.40	0.63
18.00	1	3.66	1.91

CHI-SQUARE= 12.1756
0.950 QUANTILE FOR CHI-SQUARE WITH 8 DEGREES OF FREEDOM= 15.5118

GENERALIZED POISSON

THE ESTIMATE OF N= 29
THE ESTIMATE OF ALPHA= 0.4135D+00
THE ESTIMATE OF PHI= 0.3511D-01
NUMBER OF ITERATIONS= 7

TAU	OBS	EXPECTED(COND)	SD(COND)
28.00	4	4.09	2.02

14.00	3	2.55	1.60
1.00	0	0.79	0.89
4.00	2	1.33	1.15
2.00	0	0.95	0.98
5.00	1	1.32	1.15
3.00	2	1.02	1.01
1.00	1	0.57	0.76
2.00	1	0.72	0.85
18.00	1	1.67	1.29

THE CUMULATIVE NUMBER OF ERRORS OBSERVED=0.150000D+02

CHI-SQUARE= 3.8823
0.950 QUANTILE FOR CHI-SQUARE WITH 7 DEGREES OF FREEDOM= 14.0702

IBM POISSON

THE ESTIMATE OF PHI=0.116222D-02
NUMBER OF ITERATIONS= 10

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS= 173

TAU	OBS	EXPECTED(COND)	SD(COND)
28.00	4	5.58	2.36
14.00	3	2.73	1.65
1.00	0	0.19	0.44
4.00	2	0.77	0.88
2.00	0	0.38	0.62
5.00	1	0.95	0.98
3.00	2	0.57	0.75
1.00	1	0.19	0.43
2.00	1	0.37	0.61
18.00	1	3.30	1.82

CHI-SQUARE=0.128045D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 8 DEGREES OF FREEDOM= 15.5118

BINOMIAL

THE ESTIMATE OF N= 30
THE ESTIMATE OF A= 0.5995D-02

TAU	OBS	EXPECTED(COND)	SD(COND)
28.00	4	4.62	2.15
14.00	3	2.08	1.44
1.00	0	0.14	0.37
4.00	2	0.54	0.74
2.00	0	0.25	0.50
5.00	1	0.62	0.79
3.00	2	0.35	0.60
1.00	1	0.11	0.33

2.00	1	0.20	0.45
18.00	1	1.63	1.28

CHI-SQUARE= 23.5173
0.950 QUANTILE FOR CHI-SQUARE WITH 8 DEGREES OF FREEDOM= 15.5118

IBM POISSON WITH VARIABLE ALPHA

APS ATZ SD

GEOMETRIC POISSON

THE ESTIMATE OF K=0.111662D+01
NUMBER OF ITERATIONS= 6

THE ESTIMATE OF LAMBDA=0.253423D+00

TAU	OBS	EXPECTED(COND)	SD(COND)
6.00	1	2.04	1.43
3.00	2	1.65	1.29
2.00	2	1.45	1.20
2.00	4	1.80	1.34
4.00	3	5.06	2.25

CHI-SQUARE=0.431954D+01
0.950 QUANTILE FOR CHI-SQUARE WITH 3 DEGREES OF FREEDOM= 7.8167

JELINSKI-MORANDA

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= -1
THE ESTIMATE OF B=-0.1103D+00
NUMBER OF ITERATIONS= 4

TAU	OBS	EXPECTED(COND)	SD(COND)
6.00	1	2.04	1.43
3.00	2	1.65	1.29
2.00	2	1.45	1.20
2.00	4	1.80	1.34
4.00	3	5.06	2.25

CHI-SQUARE= 4.3195
0.950 QUANTILE FOR CHI-SQUARE WITH 3 DEGREES OF FREEDOM= 7.8167

GENERALIZED POISSON

IBM POISSON

THE ESTIMATE OF PHI=0.469369D-04
NUMBER OF ITERATIONS= 9

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS= 7686

TAU	OBS	EXPECTED(COND)	SD(COND)
6.00	1	4.24	2.06
3.00	2	2.12	1.46
2.00	2	1.41	1.19
2.00	4	1.41	1.19
4.00	3	2.82	1.68

CHI-SQUARE=0.747940D+01
0.950 QUANTILE FOR CHI-SQUARE WITH 3 DEGREES OF FREEDOM= 7.8167

BINOMIAL

THE ESTIMATE OF N= 5
THE ESTIMATE OF A= 0.1832D-13

TAU	OBS	EXPECTED(COND)	SD(COND)
6.00	1	0.00	0.00
3.00	2	0.00	0.00
2.00	2	0.00	0.00
2.00	4	-0.00	0.00
4.00	3	-0.00	0.00

CHI-SQUARE=***********
0.950 QUANTILE FOR CHI-SQUARE WITH 3 DEGREES OF FREEDOM= 7.8167

IBM POISSON WITH VARIABLE ALPHA

APS ATZ ST

GEOMETRIC POISSON

THE ESTIMATE OF K=0.871296D+00
NUMBER OF ITERATIONS= 5

THE ESTIMATE OF LAMBDA=0.788882D+00

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	1	0.79	0.89
3.00	2	1.81	1.34
1.00	0	0.45	0.67
8.00	2	2.06	1.43
15.00	1	0.89	0.94

CHI-SQUARE=0.545886D+00
0.950 QUANTILE FOR CHI-SQUARE WITH 3 DEGREES OF FREEDOM= 7.8167

JELINSKI-MORANDA

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= 6
THE ESTIMATE OF B= 0.1378D+00
NUMBER OF ITERATIONS= 3

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	1	0.79	0.89
3.00	2	1.81	1.34
1.00	0	0.45	0.67
8.00	2	2.06	1.43
15.00	1	0.89	0.94

CHI-SQUARE= 0.5459
0.950 QUANTILE FOR CHI-SQUARE WITH 3 DEGREES OF FREEDOM= 7.8167

GENERALIZED POISSON

THE ESTIMATE OF N= 7
THE ESTIMATE OF ALPHA= 0.1031D+01
THE ESTIMATE OF PHI= 0.9970D-01
NUMBER OF ITERATIONS= 12

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	1	0.66	0.81
3.00	2	1.73	1.32
1.00	0	0.46	0.68
8.00	2	2.20	1.48
15.00	1	0.95	0.98

THE CUMULATIVE NUMBER OF ERRORS OBSERVED=0.600000D+01

CHI-SQUARE= 0.6998
0.950 QUANTILE FOR CHI-SQUARE WITH 2 DEGREES OF FREEDOM= 5.9948

IBM POISSON

THE ESTIMATE OF PHI=0.103584D+00
NUMBER OF ITERATIONS= 6

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS= 7

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	1	0.75	0.87
3.00	2	1.75	1.32
1.00	0	0.54	0.74
8.00	2	1.89	1.38
15.00	1	1.01	1.00

CHI-SQUARE=0.668956D+00
0.950 QUANTILE FOR CHI-SQUARE WITH 3 DEGREES OF FREEDOM= 7.8167

BINOMIAL

THE ESTIMATE OF N= 6
THE ESTIMATE OF A= 0.1564D+00

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	1	0.87	0.93
3.00	2	1.87	1.37
1.00	0	0.43	0.66
8.00	2	2.14	1.46
15.00	1	0.90	0.95

CHI-SQUARE= 0.4829
0.950 QUANTILE FOR CHI-SQUARE WITH 3 DEGREES OF FREEDOM= 7.8167

IBM POISSON WITH VARIABLE ALPHA

APS ATZ IN
APS AAZ IT

GEOMETRIC POISSON

THE ESTIMATE OF K=0.964134D+00
NUMBER OF ITERATIONS= 5

THE ESTIMATE OF LAMBDA=0.732366D+00

TAU	OBS	EXPECTED(COND)	SD(COND)
3.00	1	2.12	1.46
3.00	3	1.90	1.38
3.00	1	1.70	1.30
8.00	2	3.72	1.93
5.00	4	1.83	1.35
1.00	0	0.33	0.57
9.00	3	2.47	1.57
3.00	1	0.66	0.81
7.00	2	1.28	1.13
2.00	1	0.31	0.56
29.00	1	2.67	1.64

CHI-SQUARE=0.848494D+01
0.950 QUANTILE FOR CHI-SQUARE WITH 9 DEGREES OF FREEDOM= 16.9252

JELINSKI-MORANDA

THE ESTIMATE OF N= 21
THE ESTIMATE OF ALPHA= 0.10000D+01
THE ESTIMATE OF PHI= 0.3476D-01
NUMBER OF ITERATIONS= 7

TAU	OBS	EXPECTED(COND)	SD(COND)
3.00	1	2.15	1.47
3.00	3	2.05	1.43
3.00	1	1.73	1.32
8.00	2	4.07	2.02
5.00	4	2.19	1.48
1.00	0	0.40	0.64
9.00	3	2.70	1.64
3.00	1	0.69	0.83
7.00	2	1.13	1.06
2.00	1	0.25	0.50
29.00	1	1.64	1.28

CHI-SQUARE= 7.6318
0.950 QUANTILE FOR CHI-SQUARE WITH 9 DEGREES OF FREEDOM= 16.9252

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= 20
THE ESTIMATE OF B= 0.3653D-01
NUMBER OF ITERATIONS= 2

TAU	OBS	EXPECTED(COND)	SD(COND)
3.00	1	2.12	1.46
3.00	3	1.90	1.38
3.00	1	1.70	1.30
8.00	2	3.72	1.93
5.00	4	1.83	1.35
1.00	0	0.33	0.57
9.00	3	2.47	1.57
3.00	1	0.66	0.81
7.00	2	1.28	1.13
2.00	1	0.31	0.56
29.00	1	2.67	1.64

CHI-SQUARE= 8.4849
0.950 QUANTILE FOR CHI-SQUARE WITH 9 DEGREES OF FREEDOM= 16.9252

GENERALIZED POISSON

THE ESTIMATE OF N= 25
THE ESTIMATE OF ALPHA= 0.5845D+00
THE ESTIMATE OF PHI= 0.4765D-01
NUMBER OF ITERATIONS= 10

TAU	OBS	EXPECTED(COND)	SD(COND)
3.00	1	2.24	1.50
3.00	3	2.15	1.47
3.00	1	1.88	1.37
8.00	2	3.01	1.73
5.00	4	2.04	1.43
1.00	0	0.75	0.87
9.00	3	2.19	1.48
3.00	1	0.97	0.98
7.00	2	1.29	1.14
2.00	1	0.55	0.74
29.00	1	1.95	1.40

THE CUMULATIVE NUMBER OF ERRORS OBSERVED=0.190000D+02

CHI-SQUARE= 5.9170
0.950 QUANTILE FOR CHI-SQUARE WITH 8 DEGREES OF FREEDOM= 15.5118

IBM POISSON

THE ESTIMATE OF PHI=0.348943D-01
NUMBER OF ITERATIONS= 4

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS= 22

TAU	OBS	EXPECTED(COND)	SD(COND)
3.00	1	2.19	1.48
3.00	3	2.09	1.44
3.00	1	1.78	1.34
8.00	2	3.87	1.97
5.00	4	2.22	1.49
1.00	0	0.44	0.66
9.00	3	2.64	1.63
3.00	1	0.77	0.88
7.00	2	1.25	1.12
2.00	1	0.32	0.57
29.00	1	1.71	1.31

CHI-SQUARE=0.647527D+01
0.950 QUANTILE FOR CHI-SQUARE WITH 9 DEGREES OF FREEDOM= 16.9252

BINOMIAL

THE ESTIMATE OF N= 20
THE ESTIMATE OF A= 0.3340D-01

TAU	OBS	EXPECTED(COND)	SD(COND)
3.00	1	1.94	1.39
3.00	3	1.85	1.36
3.00	1	1.56	1.25
8.00	2	3.61	1.90
5.00	4	2.06	1.43
1.00	0	0.31	0.56
9.00	3	2.44	1.56
3.00	1	0.61	0.78
7.00	2	1.12	1.06
2.00	1	0.22	0.47
29.00	1	1.48	1.22

CHI-SQUARE= 8.2558
0.950 QUANTILE FOR CHI-SQUARE WITH 9 DEGREES OF FREEDOM= 16.9252

IBM POISSON WITH VARIABLE ALPHA

APS AAZ SD

GEOMETRIC POISSON

THE ESTIMATE OF K=0.959392D+00
NUMBER OF ITERATIONS= 5

THE ESTIMATE OF LAMBDA=0.435794D+00

TAU	OBS	EXPECTED(COND)	SD(COND)
6.00	1	2.36	1.54
2.00	0	0.67	0.82
7.00	3	1.94	1.39
2.00	2	0.46	0.68
3.00	2	0.62	0.79
8.00	0	1.32	1.15
16.00	1	1.63	1.28

CHI-SQUARE=0.118482D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 5 DEGREES OF FREEDOM= 11.0733

JELINSKI-MORANDA

THE ESTIMATE OF N= 10
THE ESTIMATE OF ALPHA= 0.1000D+01
THE ESTIMATE OF PHI= 0.4285D-01
NUMBER OF ITERATIONS= 20

TAU	OBS	EXPECTED(COND)	SD(COND)
6.00	1	2.68	1.64
2.00	0	0.81	0.90

7.00	3	2.52	1.59
2.00	2	0.64	0.80
3.00	2	0.57	0.75
8.00	0	0.83	0.91
16.00	1	0.97	0.98

CHI-SQUARE= 9.3311
0.950 QUANTILE FOR CHI-SQUARE WITH 5 DEGREES OF FREEDOM= 11.0733

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= 11
THE ESTIMATE OF B= 0.4146D-01
NUMBER OF ITERATIONS= 2

TAU	OBS	EXPECTED(COND)	SD(COND)
6.00	1	2.36	1.54
2.00	0	0.67	0.82
7.00	3	1.94	1.39
2.00	2	0.46	0.68
3.00	2	0.62	0.79
8.00	0	1.32	1.15
16.00	1	1.63	1.28

CHI-SQUARE= 11.8482
0.950 QUANTILE FOR CHI-SQUARE WITH 5 DEGREES OF FREEDOM= 11.0733

GENERALIZED POISSON

THE ESTIMATE OF N= 16
THE ESTIMATE OF ALPHA= 0.1776D+00
THE ESTIMATE OF FHI= 0.8432D-01
NUMBER OF ITERATIONS= 8

TAU	OBS	EXPECTED(COND)	SD(COND)
6.00	1	1.83	1.35
2.00	0	1.41	1.19
7.00	3	1.64	1.28
2.00	2	1.22	1.10
3.00	2	1.00	1.00
8.00	0	0.95	0.98
16.00	1	0.94	0.97

THE CUMULATIVE NUMBER OF ERRORS OBSERVED=0.900000D+01

CHI-SQUARE= 5.3483
0.950 QUANTILE FOR CHI-SQUARE WITH 4 DEGREES OF FREEDOM= 9.4917

IBM POISSON

THE ESTIMATE OF PHI=0.467260D-01
NUMBER OF ITERATIONS= 5

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS= 11

TAU	OBS	EXPECTED(COND)	SD(COND)
6.00	1	2.68	1.64
2.00	0	0.89	0.94
7.00	3	2.48	1.58
2.00	2	0.70	0.84
3.00	2	0.63	0.79
8.00	0	0.86	0.93
16.00	1	0.92	0.96

CHI-SQUARE=0.827155D+01
0.950 QUANTILE FOR CHI-SQUARE WITH 5 DEGREES OF FREEDOM= 11.0733

BINOMIAL

THE ESTIMATE OF N= 10
THE ESTIMATE OF A= 0.38120-01

TAU	OBS	EXPECTED(COND)	SD(COND)
6.00	1	2.11	1.45
2.00	0	0.69	0.83
7.00	3	2.19	1.48
2.00	2	0.46	0.68
3.00	2	0.47	0.68
8.00	0	0.61	0.78
16.00	1	1.07	1.03

CHI-SQUARE= 12.2701
0.950 QUANTILE FOR CHI-SQUARE WITH 5 DEGREES OF FREEDOM= 11.0733

IBM POISSON WITH VARIABLE ALPHA

APS AAZ ST

GEOMETRIC POISSON

THE ESTIMATE OF K=0.932682D+00
NUMBER OF ITERATIONS= 5

THE ESTIMATE OF LAMBDA=0.502143D+00

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	1	0.50	0.71
2.00	1	0.91	0.95

4.00	1	1.47	1.21
8.00	1	1.96	1.40
4.00	0	0.64	0.80
5.00	3	0.58	0.76
6.00	0	0.48	0.69
10.00	0	0.46	0.68

CHI-SQUARE=0.127011D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 6 DEGREES OF FREEDOM= 12.5961

JELINSKI-MORANDA

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= 7
THE ESTIMATE OF B= 0.69690-01
NUMBER OF ITERATIONS= 2

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	1	0.50	0.71
2.00	1	0.91	0.95
4.00	1	1.47	1.21
8.00	1	1.96	1.40
4.00	0	0.64	0.80
5.00	3	0.58	0.76
6.00	0	0.48	0.69
10.00	0	0.46	0.68

CHI-SQUARE= 12.7011
0.950 QUANTILE FOR CHI-SQUARE WITH 6 DEGREES OF FREEDOM= 12.5961

GENERALIZED POISSON

IBM POISSON

THE ESTIMATE OF PHI=-.498151D-04
NUMBER OF ITERATIONS= 14

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS= -1818

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	1	0.17	0.42
2.00	1	0.35	0.59
4.00	1	0.70	0.84
8.00	1	1.40	1.18
4.00	0	0.70	0.84
5.00	3	0.88	0.94
6.00	0	1.05	1.03
10.00	0	1.75	1.32

CHI-SQUARE=0.140242D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 6 DEGREES OF FREEDOM= 12.5961

BINOMIAL

THE ESTIMATE OF N= 7
THE ESTIMATE OF A= 0.7355D-01

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	1	0.50	0.71
2.00	1	0.83	0.91
4.00	1	1.30	1.14
8.00	1	1.83	1.35
4.00	0	0.79	0.89
5.00	3	0.96	0.98
6.00	0	0.04	0.19
10.00	0	0.05	0.23

CHI-SQUARE= 6.2246
0.950 QUANTILE FOR CHI-SQUARE WITH 6 DEGREES OF FREEDOM= 12.5961

IBM POISSON WITH VARIABLE ALPHA

APS AAZ IN

GEOMETRIC POISSON

THE ESTIMATE OF K=0.688782D+00
NUMBER OF ITERATIONS= 4

THE ESTIMATE OF LAMBDA=0.157404D+01

TAU	OBS	EXPECTED(COND)	SD(COND)
3.00	3	3.40	1.85
4.00	2	1.28	1.13
2.00	0	0.20	0.44
3.00	0	0.12	0.34

CHI-SQUARE=0.766437D+00
0.950 QUANTILE FOR CHI-SQUARE WITH 2 DEGREES OF FREEDOM= 5.9948

JELINSKI-MORANDA

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= 5
THE ESTIMATE OF B= 0.3728D+00

NUMBER OF ITERATIONS= 4

TAU	OBS	EXPECTED(COND)	SD(COND)
3.00	3	3.40	1.85
4.00	2	1.28	1.13
2.00	0	0.20	0.44
3.00	0	0.12	0.34

CHI-SQUARE= 0.7664
0.950 QUANTILE FOR CHI-SQUARE WITH 2 DEGREES OF FREEDOM= 5.9948

GENERALIZED POISSON

IBM POISSON

THE ESTIMATE OF PHI=0.425279D-04
NUMBER OF ITERATIONS= 9

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS= 4853

TAU	OBS	EXPECTED(COND)	SD(COND)
3.00	3	1.25	1.12
4.00	2	1.67	1.29
2.00	0	0.83	0.91
3.00	0	1.25	1.12

CHI-SQUARE=0.459612D+01
0.950 QUANTILE FOR CHI-SQUARE WITH 2 DEGREES OF FREEDOM= 5.9948

BINOMIAL

THE ESTIMATE OF N= 5
THE ESTIMATE OF A= 0.29750D+00

TAU	OBS	EXPECTED(COND)	SD(COND)
3.00	3	3.14	1.77
4.00	2	1.62	1.27
2.00	0	0.15	0.38
3.00	0	0.19	0.44

CHI-SQUARE= 0.4358
0.950 QUANTILE FOR CHI-SQUARE WITH 2 DEGREES OF FREEDOM= 5.9948

IBM POISSON WITH VARIABLE ALPHA

APS MEZ IT

GEOMETRIC POISSON

THE ESTIMATE OF K=0.977927D+00
NUMBER OF ITERATIONS= 5

THE ESTIMATE OF LAMBDA=0.753067D+00

TAU	OBS	EXPECTED(COND)	SD(COND)
14.00	1	9.16	3.03
9.00	8	4.54	2.13
2.00	6	0.89	0.94
2.00	2	0.85	0.92
1.00	4	0.41	0.64
2.00	0	0.80	0.89
5.00	1	1.84	1.36
1.00	0	0.34	0.59
7.00	1	2.21	1.49
5.00	1	1.38	1.17
2.00	1	0.51	0.71
2.00	1	0.49	0.70
11.00	2	2.33	1.53
22.00	1	3.24	1.80

CHI-SQUARE=0.768464D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 12 DEGREES OF FREEDOM= 21.0297

JELINSKI-MORANDA

THE ESTIMATE OF N= 33
THE ESTIMATE OF ALPHA= 0.1000D+01
THE ESTIMATE OF PHI= 0.2238D-01
NUMBER OF ITERATIONS= 15

TAU	OBS	EXPECTED(COND)	SD(COND)
14.00	1	10.39	3.22
9.00	8	6.48	2.55
2.00	6	1.26	1.12
2.00	2	1.22	1.10
1.00	4	0.41	0.64
2.00	0	0.77	0.88
5.00	1	1.36	1.17
1.00	0	0.25	0.50
7.00	1	1.59	1.26
5.00	1	1.03	1.01
2.00	1	0.37	0.60
2.00	1	0.32	0.57
11.00	2	1.52	1.23
22.00	1	2.05	1.43

CHI-SQUARE= 63.5094
0.950 QUANTILE FOR CHI-SQUARE WITH 12 DEGREES OF FREEDOM= 21.0297

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= 34
THE ESTIMATE OF B= 0.2232D-01
NUMBER OF ITERATIONS= 2

TAU	OBS	EXPECTED(COND)	SD(COND)
14.00	1	9.16	3.03
9.00	8	4.54	2.13
2.00	6	0.89	0.94
2.00	2	0.85	0.92
1.00	4	0.41	0.64
2.00	0	0.80	0.89
5.00	1	1.84	1.36
1.00	0	0.34	0.59
7.00	1	2.21	1.49
5.00	1	1.38	1.17
2.00	1	0.51	0.71
2.00	1	0.49	0.70
11.00	2	2.33	1.53
22.00	1	3.24	1.80

CHI-SQUARE= 76.8464
0.950 QUANTILE FOR CHI-SQUARE WITH 12 DEGREES OF FREEDOM= 21.0297

GENERALIZED POISSON

THE ESTIMATE OF N= 35
THE ESTIMATE OF ALPHA= 0.5048D-01
THE ESTIMATE OF PHI= 0.1111D+00
NUMBER OF ITERATIONS= 5

TAU	OBS	EXPECTED(COND)	SD(COND)
14.00	1	4.38	2.09
9.00	8	4.16	2.04
2.00	6	3.40	1.84
2.00	2	3.28	1.81
1.00	4	2.17	1.47
2.00	0	2.13	1.46
5.00	1	1.63	1.28
1.00	0	1.39	1.18
7.00	1	1.42	1.19
5.00	1	1.27	1.13
2.00	1	1.10	1.05
2.00	1	0.98	0.99
11.00	2	0.95	0.97
22.00	1	0.72	0.85

THE CUMULATIVE NUMBER OF ERRORS OBSERVED=0.290000D+02

CHI-SQUARE= 15.4207
0.950 QUANTILE FOR CHI-SQUARE WITH 11 DEGREES OF FREEDOM= 19.6806

IBM POISSON

THE ESTIMATE OF PHI=0.427757D-01
NUMBER OF ITERATIONS= 7

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS= 28

TAU	OBS	EXPECTED(COND)	SD(COND)
14.00	1	12.87	3.59
9.00	8	8.82	2.97
2.00	6	1.94	1.39
2.00	2	1.85	1.36
1.00	4	0.56	0.75
2.00	0	1.02	1.01
5.00	1	1.40	1.18
1.00	0	0.26	0.51
7.00	1	1.36	1.16
5.00	1	0.81	0.90
2.00	1	0.26	0.51
2.00	1	0.18	0.42
11.00	2	0.44	0.66
22.00	1	-0.53	0.73

CHI-SQUARE=0.491077D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 12 DEGREES OF FREEDOM= 21.0297

BINOMIAL

THE ESTIMATE OF N= 12
THE ESTIMATE OF A= 0.6721D-11

TAU	OBS	EXPECTED(COND)	SD(COND)
14.00	1	0.00	0.00
9.00	8	0.00	0.00
2.00	6	0.00	0.00
2.00	2	-0.00	0.00
1.00	4	-0.00	0.00
2.00	0	-0.00	0.00
5.00	1	-0.00	0.00
1.00	0	-0.00	0.00
7.00	1	-0.00	0.00
5.00	1	-0.00	0.00
2.00	1	-0.00	0.00
2.00	1	-0.00	0.00
11.00	2	-0.00	0.00
22.00	1	-0.00	0.00

CHI-SQUARE=**********
0.950 QUANTILE FOR CHI-SQUARE WITH 12 DEGREES OF FREEDOM= 21.0297

IBM POISSON WITH VARIABLE ALPHA

APS MEZ SD

GEOMETRIC POISSON

THE ESTIMATE OF K=0.854263D+00
NUMBER OF ITERATIONS= 5

THE ESTIMATE OF LAMBDA=0.131550D+01

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	4	1.32	1.15
4.00	1	3.60	1.90
2.00	1	1.11	1.05
6.00	1	1.83	1.35
3.00	1	0.44	0.66
21.00	1	0.70	0.84

CHI-SQUARE=0.859647D+01
0.950 QUANTILE FOR CHI-SQUARE WITH 4 DEGREES OF FREEDOM= 9.4917

JELINSKI-MORANDA

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= 9
THE ESTIMATE OF B= 0.1575D+00
NUMBER OF ITERATIONS= 3

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	4	1.32	1.15
4.00	1	3.60	1.90
2.00	1	1.11	1.05
6.00	1	1.83	1.35
3.00	1	0.44	0.66
21.00	1	0.70	0.84

CHI-SQUARE= 8.5965
0.950 QUANTILE FOR CHI-SQUARE WITH 4 DEGREES OF FREEDOM= 9.4917

GENERALIZED POISSON

THE ESTIMATE OF N= 16
THE ESTIMATE OF ALPHA=-0.3098D+00
THE ESTIMATE OF PHI= 0.1967D+00
NUMBER OF ITERATIONS= 15

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	4	3.13	1.77
4.00	1	1.65	1.29
2.00	1	1.57	1.25
6.00	1	1.01	1.00
3.00	1	1.11	1.05
21.00	1	0.53	0.73

THE CUMULATIVE NUMBER OF ERRORS OBSERVED=0.900000D+01

CHI-SQUARE= 1.1372
0.950 QUANTILE FOR CHI-SQUARE WITH 3 DEGREES OF FREEDOM= 7.8167

IBM POISSON

THE ESTIMATE OF PHI=0.171108D+00
NUMBER OF ITERATIONS= 6

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS= 10

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	4	1.67	1.29
4.00	1	3.56	1.89
2.00	1	1.17	1.08
6.00	1	1.86	1.36
3.00	1	0.75	0.87
21.00	1	0.73	0.86

CHI-SQUARE=0.570299D+01
0.950 QUANTILE FOR CHI-SQUARE WITH 4 DEGREES OF FREEDOM= 9.4917

BINOMIAL

THE ESTIMATE OF N= 7
THE ESTIMATE OF A= 0.5136D+00

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	4	2.99	1.73
4.00	1	3.00	1.73
2.00	1	1.57	1.25
6.00	1	1.38	1.17
3.00	1	0.35	0.59
21.00	1	-0.56	0.75

CHI-SQUARE= -1.1557
0.950 QUANTILE FOR CHI-SQUARE WITH 4 DEGREES OF FREEDOM= 9.4917

IBM POISSON WITH VARIABLE ALPHA

APS MEZ ST

GEOMETRIC POISSON

THE ESTIMATE OF K=0.834874D+00
NUMBER OF ITERATIONS= 5

THE ESTIMATE OF LAMBDA=0.117811D+01

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	1	1.18	1.09
3.00	3	2.49	1.58
1.00	0	0.57	0.76
5.00	2	1.72	1.31
12.00	1	1.04	1.02

CHI-SQUARE=0.750641D+00
0.950 QUANTILE FOR CHI-SQUARE WITH 3 DEGREES OF FREEDOM= 7.8167

JELINSKI-MORANDA

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= 7
THE ESTIMATE OF B= 0.18050D+00
NUMBER OF ITERATIONS= 3

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	1	1.18	1.09
3.00	3	2.49	1.58
1.00	0	0.57	0.76
5.00	2	1.72	1.31
12.00	1	1.04	1.02

CHI-SQUARE= 0.7506
0.950 QUANTILE FOR CHI-SQUARE WITH 3 DEGREES OF FREEDOM= 7.8167

GENERALIZED POISSON

IBM POISSON

THE ESTIMATE OF PHI=0.135399D+00
NUMBER OF ITERATIONS= 6

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS= 8

TAU	OBS	EXPECTED(COND)	SD(COND)

1.00	1	1.12	1.06
3.00	3	2.23	1.49
1.00	0	0.72	0.85
5.00	2	1.71	1.31
12.00	1	1.08	1.04

CHI-SQUARE=0.105318D+01
0.950 QUANTILE FOR CHI-SQUARE WITH 3 DEGREES OF FREEDOM= 7.8167

BINOMIAL

THE ESTIMATE OF N= 7
THE ESTIMATE OF A= 0.1975D+00

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	1	1.27	1.13
3.00	3	2.73	1.65
1.00	0	0.56	0.75
5.00	2	1.95	1.40
12.00	1	1.00	1.00

CHI-SQUARE= 0.6437
0.950 QUANTILE FOR CHI-SQUARE WITH 3 DEGREES OF FREEDOM= 7.8167

IBM POISSON WITH VARIABLE ALPHA

APS MEZ IN
APS HTZ IT

GEOMETRIC POISSON

THE ESTIMATE OF K=0.101342D+01
NUMBER OF ITERATIONS= 5

THE ESTIMATE OF LAMBDA=0.267135D+00

TAU	OBS	EXPECTED(COND)	SD(COND)
5.00	1	1.37	1.17
7.00	1	2.08	1.44
5.00	2	1.61	1.27
1.00	2	0.34	0.58
3.00	2	1.03	1.02
1.00	0	0.35	0.59
6.00	2	2.22	1.49
5.00	1	1.99	1.41

CHI-SQUARE=0.108058D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 6 DEGREES OF FREEDOM= 12.5961

JELINSKI-MORANDA

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= -19
THE ESTIMATE OF B=-0.1333D-01
NUMBER OF ITERATIONS= 3

TAU	OBS	EXPECTED(COND)	SD(COND)
5.00	1	1.37	1.17
7.00	1	2.08	1.44
5.00	2	1.61	1.27
1.00	2	0.34	0.58
3.00	2	1.03	1.02
1.00	0	0.35	0.59
6.00	2	2.22	1.49
5.00	1	1.99	1.41

CHI-SQUARE= 10.8058
0.950 QUANTILE FOR CHI-SQUARE WITH 6 DEGREES OF FREEDOM= 12.5961

GENERALIZED POISSON

THE ESTIMATE OF N= 153
THE ESTIMATE OF ALPHA= 0.1493D+00
THE ESTIMATE OF PHI= 0.7735D-02
NUMBER OF ITERATIONS= 13

TAU	OBS	EXPECTED(COND)	SD(COND)
5.00	1	1.50	1.23
7.00	1	1.57	1.25
5.00	2	1.48	1.22
1.00	2	1.15	1.07
3.00	2	1.33	1.15
1.00	0	1.12	1.06
6.00	2	1.45	1.21
5.00	1	1.39	1.18

THE CUMULATIVE NUMBER OF ERRORS OBSERVED=0.110000D+02

CHI-SQUARE= 2.9590
0.950 QUANTILE FOR CHI-SQUARE WITH 5 DEGREES OF FREEDOM= 11.0733

IBM POISSON

THE ESTIMATE OF PHI=0.555356D-04
NUMBER OF ITERATIONS= 11

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS= 3898

TAU	OBS	EXPECTED(COND)	SD(COND)
5.00	1	1.67	1.29
7.00	1	2.34	1.53
5.00	2	1.67	1.29
1.00	2	0.33	0.58
3.00	2	1.00	1.00
1.00	0	0.33	0.58
6.00	2	2.00	1.41
5.00	1	1.66	1.29

CHI-SQUARE=0.110256D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 6 DEGREES OF FREEDOM= 12.5961

BINOMIAL

IBM POISSON WITH VARIABLE ALPHA

APS HTZ SD

GEOMETRIC POISSON

THE ESTIMATE OF K=0.900641D+00
NUMBER OF ITERATIONS= 4

THE ESTIMATE OF LAMBDA=0.220806D+01

TAU	OBS	EXPECTED(COND)	SD(COND)
7.00	7	11.54	3.40
1.00	7	1.06	1.03
3.00	4	2.59	1.61
4.00	1	2.40	1.55
6.00	1	2.16	1.47
1.00	0	0.25	0.50

CHI-SQUARE=0.374639D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 4 DEGREES OF FREEDOM= 9.4917

JELINSKI-MORANDA

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= 22
THE ESTIMATE OF B= 0.1046D+00
NUMBER OF ITERATIONS= 3

TAU	OBS	EXPECTED(COND)	SD(COND)

7.00	7	11.54	3.40
1.00	7	1.06	1.03
3.00	4	2.59	1.61
4.00	1	2.40	1.55
6.00	1	2.16	1.47
1.00	0	0.25	0.50

CHI-SQUARE= 37.4639
0.950 QUANTILE FOR CHI-SQUARE WITH 4 DEGREES OF FREEDOM= 9.4917

GENERALIZED POISSON

THE ESTIMATE OF N= 16
THE ESTIMATE OF ALPHA=-0.3081D+00
THE ESTIMATE OF PHI= 0.1165D+01
NUMBER OF ITERATIONS= 9

TAU	OBS	EXPECTED(COND)	SD(COND)
7.00	7	10.41	3.23
1.00	7	11.97	3.46
3.00	4	3.55	1.89
4.00	1	0.21	0.46
6.00	1	-1.82	1.35
1.00	0	-4.33	2.08

THE CUMULATIVE NUMBER OF ERRORS OBSERVED=0.200000D+02

CHI-SQUARE= -2.5733
0.950 QUANTILE FOR CHI-SQUARE WITH 3 DEGREES OF FREEDOM= 7.8167

IBM POISSON

THE ESTIMATE OF PHI=-.408154D-04
NUMBER OF ITERATIONS= 11

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS= -11390

TAU	OBS	EXPECTED(COND)	SD(COND)
7.00	7	6.36	2.52
1.00	7	0.91	0.95
3.00	4	2.73	1.65
4.00	1	3.64	1.91
6.00	1	5.46	2.34
1.00	0	0.91	0.95

CHI-SQUARE=0.479658D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 4 DEGREES OF FREEDOM= 9.4917

BINOMIAL

THE ESTIMATE OF N=   16
THE ESTIMATE OF A= 0.7325D+00

TAU	OBS	EXPECTED(COND)	SD(COND)
7.00	7	16.39	4.05
1.00	7	4.93	2.22
3.00	4	2.22	1.49
4.00	1	-1.43	1.19
6.00	1	-2.48	1.57
1.00	0	-1.82	1.35

CHI-SQUARE=   -3.1396
0.950 QUANTILE FOR CHI-SQUARE WITH   4 DEGREES OF FREEDOM=   9.4917

IBM POISSON WITH VARIABLE ALPHA

APS HTZ ST

GEOMETRIC POISSON

THE ESTIMATE OF K=0.925117D+00
NUMBER OF ITERATIONS= 5

THE ESTIMATE OF LAMBDA=0.122471D+01

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	1	1.22	1.11
1.00	1	1.13	1.06
2.00	2	2.02	1.42
2.00	1	1.73	1.31
3.00	2	2.14	1.46
6.00	5	3.03	1.74
7.00	2	2.14	1.46
10.00	1	1.60	1.26

CHI-SQUARE=0.188581D+01
0.950 QUANTILE FOR CHI-SQUARE WITH   6 DEGREES OF FREEDOM=   12.5961

JELINSKI-MORANDA

THE ESTIMATE OF N=   17
THE ESTIMATE OF ALPHA= 0.1000D+01
THE ESTIMATE OF PHI= 0.7048D-01
NUMBER OF ITERATIONS=   7

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	1	1.17	1.08
1.00	1	1.10	1.05
2.00	2	1.92	1.38

2.00	1	1.63	1.28
3.00	2	2.24	1.50
6.00	5	4.05	2.01
7.00	2	1.77	1.33
10.00	1	1.12	1.06

CHI-SQUARE= 0.5711
0.950 QUANTILE FOR CHI-SQUARE WITH 6 DEGREES OF FREEDOM= 12.5961

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= 16
THE ESTIMATE OF B= 0.7784D-01
NUMBER OF ITERATIONS= 2

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	1	1.22	1.11
1.00	1	1.13	1.06
2.00	2	2.02	1.42
2.00	1	1.73	1.31
3.00	2	2.14	1.46
6.00	5	3.03	1.74
7.00	2	2.14	1.46
10.00	1	1.60	1.26

CHI-SQUARE= 1.8858
0.950 QUANTILE FOR CHI-SQUARE WITH 6 DEGREES OF FREEDOM= 12.5961

GENERALIZED POISSON

THE ESTIMATE OF N= 16
THE ESTIMATE OF ALPHA= 0.1253D+01
THE ESTIMATE OF PHI= 0.5667D-01
NUMBER OF ITERATIONS= 9

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	1	0.91	0.95
1.00	1	0.85	0.92
2.00	2	1.75	1.32
2.00	1	1.48	1.22
3.00	2	2.24	1.50
6.00	5	4.81	2.19
7.00	2	1.94	1.39
10.00	1	1.01	1.00

THE CUMULATIVE NUMBER OF ERRORS OBSERVED=0.150000D+02

CHI-SQUARE= 0.2643
0.950 QUANTILE FOR CHI-SQUARE WITH 5 DEGREES OF FREEDOM= 11.0733

IBM POISSON

THE ESTIMATE OF PHI=0.697888D-01
NUMBER OF ITERATIONS= 5

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS= 17

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	1	1.21	1.10
1.00	1	1.14	1.07
2.00	2	1.94	1.39
2.00	1	1.67	1.29
3.00	2	2.22	1.49
6.00	5	3.66	1.91
7.00	2	1.74	1.32
10.00	1	1.23	1.11

CHI-SQUARE=0.920383D+00
0.950 QUANTILE FOR CHI-SQUARE WITH 6 DEGREES OF FREEDOM= 12.5961

BINOMIAL

THE ESTIMATE OF N= 17
THE ESTIMATE OF A= 0.80530-01

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	1	1.28	1.13
1.00	1	1.20	1.10
2.00	2	2.17	1.47
2.00	1	1.87	1.37
3.00	2	2.48	1.58
6.00	5	3.66	1.91
7.00	2	1.97	1.40
10.00	1	1.42	1.19

CHI-SQUARE= 1.2172
0.950 QUANTILE FOR CHI-SQUARE WITH 6 DEGREES OF FREEDOM= 12.5961

IBM POISSON WITH VARIABLE ALPHA

APS HTZ IN
APS MIZ IT

GEOMETRIC POISSON

THE ESTIMATE OF K=0.102842D+01
NUMBER OF ITERATIONS= 5

THE ESTIMATE OF LAMBDA=0.289863D+00

TAU	OBS	EXPECTED(COND)	SD(COND)
10.00	2	3.30	1.82
2.00	0	0.78	0.88
8.00	5	3.59	1.89
1.00	0	0.51	0.71
3.00	4	1.61	1.27
2.00	3	1.15	1.07
3.00	2	1.85	1.36
4.00	0	2.73	1.65
2.00	1	1.48	1.22

CHI-SQUARE=0.117533D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 7 DEGREES OF FREEDOM= 14.0702

JELINSKI-MORANDA

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= -9
THE ESTIMATE OF B=-0.28030-01
NUMBER OF ITERATIONS= 3

TAU	OBS	EXPECTED(COND)	SD(COND)
10.00	2	3.30	1.82
2.00	0	0.78	0.88
8.00	5	3.59	1.89
1.00	0	0.51	0.71
3.00	4	1.61	1.27
2.00	3	1.15	1.07
3.00	2	1.85	1.36
4.00	0	2.73	1.65
2.00	1	1.48	1.22

CHI-SQUARE= 11.7533
0.950 QUANTILE FOR CHI-SQUARE WITH 7 DEGREES OF FREEDOM= 14.0702

GENERALIZED POISSON

IBM POISSON

THE ESTIMATE OF PHI=0.310001D-04
NUMBER OF ITERATIONS= 10

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS= 8451

TAU	OBS	EXPECTED(COND)	SD(COND)
10.00	2	4.86	2.20

2.00	0	0.97	0.99
8.00	5	3.89	1.97
1.00	0	0.49	0.70
3.00	4	1.46	1.21
2.00	3	0.97	0.99
3.00	2	1.46	1.21
4.00	0	1.94	1.39
2.00	1	0.97	0.99

CHI-SQUARE=0.142827D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 7 DEGREES OF FREEDOM= 14.0702

BINOMIAL

THE ESTIMATE OF N= 4
THE ESTIMATE OF A=-0.3767D-12

TAU	OBS	EXPECTED(COND)	SD(COND)
10.00	2	-0.00	0.00
2.00	0	-0.00	0.00
8.00	5	-0.00	0.00
1.00	0	0.00	0.00
3.00	4	0.00	0.00
2.00	3	0.00	0.00
3.00	2	0.00	0.00
4.00	0	0.00	0.00
2.00	1	0.00	0.00

CHI-SQUARE=***********
0.950 QUANTILE FOR CHI-SQUARE WITH 7 DEGREES OF FREEDOM= 14.0702

IBM POISSON WITH VARIABLE ALPHA

APS MIZ SD

GEOMETRIC POISSON

THE ESTIMATE OF K=0.937144D+00
NUMBER OF ITERATIONS= 5

THE ESTIMATE OF LAMBDA=0.174624D+01

TAU	OBS	EXPECTED(COND)	SD(COND)
5.00	6	7.70	2.77
4.00	6	4.59	2.14
1.00	0	0.97	0.99
4.00	3	3.32	1.82
2.00	1	1.36	1.17
2.00	0	1.20	1.09
5.00	7	2.39	1.55
1.00	0	0.39	0.63
1.00	1	0.37	0.61

2.00	0	0.67	0.82
5.00	2	1.33	1.16
23.00	1	2.70	1.64

CHI-SQUARE=0.155187D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 10 DEGREES OF FREEDOM= 18.3111

JELINSKI-MORANDA

THE ESTIMATE OF N= 28
THE ESTIMATE OF ALPHA= 0.1000D+01
THE ESTIMATE OF PHI= 0.5649D-01
NUMBER OF ITERATIONS= 12

TAU	OBS	EXPECTED(COND)	SD(COND)
5.00	6	7.94	2.82
4.00	6	4.77	2.18
1.00	0	1.02	1.01
4.00	3	3.41	1.85
2.00	1	1.59	1.26
2.00	0	1.48	1.22
5.00	7	3.14	1.77
1.00	0	0.51	0.72
1.00	1	0.35	0.59
2.00	0	0.46	0.68
5.00	2	0.88	0.94
23.00	1	1.44	1.20

CHI-SQUARE= 12.1115
0.950 QUANTILE FOR CHI-SQUARE WITH 10 DEGREES OF FREEDOM= 18.3111

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= 28
THE ESTIMATE OF B= 0.6492D-01
NUMBER OF ITERATIONS= 2

TAU	OBS	EXPECTED(COND)	SD(COND)
5.00	6	7.70	2.77
4.00	6	4.59	2.14
1.00	0	0.97	0.99
4.00	3	3.32	1.82
2.00	1	1.36	1.17
2.00	0	1.20	1.09
5.00	7	2.39	1.55
1.00	0	0.39	0.63
1.00	1	0.37	0.61
2.00	0	0.67	0.82
5.00	2	1.33	1.16
23.00	1	2.70	1.64

CHI-SQUARE=   15.5187
0.950 QUANTILE FOR CHI-SQUARE WITH 10 DEGREES OF FREEDOM=   18.3111

GENERALIZED POISSON

APS MIZ ST

GEOMETRIC POISSON

THE ESTIMATE OF K=0.842978D+00
NUMBER OF ITERATIONS= 4

THE ESTIMATE OF LAMBDA=0.238341D+01

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	4	2.38	1.54
1.00	1	2.01	1.42
1.00	2	1.69	1.30
2.00	2	2.63	1.62
3.00	2	2.59	1.61
1.00	1	0.61	0.78
1.00	1	0.51	0.72
4.00	0	1.36	1.17
12.00	2	1.21	1.10

CHI-SQUARE=0.453956D+01
0.950 QUANTILE FOR CHI-SQUARE WITH   7 DEGREES OF FREEDOM=   14.0702

JELINSKI-MORANDA

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N=   15
THE ESTIMATE OF B= 0.1708D+00
NUMBER OF ITERATIONS=   3

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	4	2.38	1.54
1.00	1	2.01	1.42
1.00	2	1.69	1.30
2.00	2	2.63	1.62
3.00	2	2.59	1.61
1.00	1	0.61	0.78
1.00	1	0.51	0.72
4.00	0	1.36	1.17
12.00	2	1.21	1.10

CHI-SQUARE=   4.5396
0.950 QUANTILE FOR CHI-SQUARE WITH   7 DEGREES OF FREEDOM=   14.0702

GENERALIZED POISSON

THE ESTIMATE OF N= 16
THE ESTIMATE OF ALPHA= 0.5192D+00
THE ESTIMATE OF PHI= 0.1695D+00
NUMBER OF ITERATIONS= 6

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	4	2.76	1.66
1.00	1	2.25	1.50
1.00	2	1.91	1.38
2.00	2	2.01	1.42
3.00	2	1.89	1.37
1.00	1	0.90	0.95
1.00	1	0.73	0.85
4.00	0	1.14	1.07
12.00	2	1.41	1.19

THE CUMULATIVE NUMBER OF ERRORS OBSERVED=0.150000D+02

CHI-SQUARE= 2.7711
0.950 QUANTILE FOR CHI-SQUARE WITH 6 DEGREES OF FREEDOM= 12.5961

IBM POISSON

THE ESTIMATE OF PHI=0.164543D+00
NUMBER OF ITERATIONS= 4

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS= 16
APS DAZ IT

GEOMETRIC POISSON

THE ESTIMATE OF K=0.947206D+00
NUMBER OF ITERATIONS= 5

THE ESTIMATE OF LAMBDA=0.329075D+01

TAU	OBS	EXPECTED(COND)	SD(COND)
2.00	3	6.41	2.53
1.00	0	2.95	1.72
6.00	14	14.71	3.84
1.00	0	2.02	1.42
3.00	7	5.44	2.33
5.00	18	7.31	2.70
1.00	2	1.24	1.11
1.00	0	1.17	1.08
2.00	5	2.17	1.47
4.00	3	3.69	1.92
5.00	3	3.61	1.90

1.00	0	0.61	0.78
1.00	0	0.58	0.76
13.00	3	5.27	2.29
3.00	0	0.77	0.88
4.00	1	0.85	0.92
1.00	0	0.19	0.43

CHI-SQUARE=0.316067D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 15 DEGREES OF FREEDOM= 24.9997

JELINSKI-MORANDA

THE ESTIMATE OF N= 62
THE ESTIMATE OF ALPHA= 0.1000D+01
THE ESTIMATE OF PHI= 0.4703D-01
NUMBER OF ITERATIONS= 4

TAU	OBS	EXPECTED(COND)	SD(COND)
2.00	3	5.85	2.42
1.00	0	2.88	1.70
6.00	14	16.42	4.05
1.00	0	2.50	1.58
3.00	7	6.66	2.58
5.00	18	10.15	3.19
1.00	2	1.33	1.15
1.00	0	0.90	0.95
2.00	5	1.71	1.31
4.00	3	2.67	1.63
5.00	3	2.16	1.47
1.00	0	0.38	0.62
1.00	0	0.34	0.58
13.00	3	3.78	1.94
3.00	0	0.59	0.77
4.00	1	0.60	0.77
1.00	0	0.10	0.32

CHI-SQUARE= 22.9963
0.950 QUANTILE FOR CHI-SQUARE WITH 15 DEGREES OF FREEDOM= 24.9997

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= 62
THE ESTIMATE OF B= 0.5424D-01
NUMBER OF ITERATIONS= 2

TAU	OBS	EXPECTED(COND)	SD(COND)
2.00	3	6.41	2.53
1.00	0	2.95	1.72
6.00	14	14.71	3.84
1.00	0	2.02	1.42
3.00	7	5.44	2.33

5.00	18	7.31	2.70
1.00	2	1.24	1.11
1.00	0	1.17	1.08
2.00	5	2.17	1.47
4.00	3	3.69	1.92
5.00	3	3.61	1.90
1.00	0	0.61	0.78
1.00	0	0.58	0.76
13.00	3	5.27	2.29
3.00	0	0.77	0.88
4.00	1	0.85	0.92
1.00	0	0.19	0.43

CHI-SQUARE= 31.6067
0.950 QUANTILE FOR CHI-SQUARE WITH 15 DEGREES OF FREEDOM= 24.9997

GENERALIZED POISSON

THE ESTIMATE OF N= 57
THE ESTIMATE OF ALPHA= 0.1524D+01
THE ESTIMATE OF PHI= 0.2899D-01
NUMBER OF ITERATIONS= 15

TAU	OBS	EXPECTED(COND)	SD(COND)
2.00	3	4.79	2.19
1.00	0	1.64	1.28
6.00	14	23.78	4.88
1.00	0	1.41	1.19
3.00	7	6.57	2.56
5.00	18	12.96	3.60
1.00	2	0.68	0.83
1.00	0	0.42	0.65
2.00	5	1.13	1.06
4.00	3	2.28	1.51
5.00	3	1.51	1.23
1.00	0	0.10	0.32
1.00	0	0.07	0.27
13.00	3	2.16	1.47
3.00	0	-0.08	0.28
4.00	1	-0.36	0.60
1.00	0	-0.07	0.27

THE CUMULATIVE NUMBER OF ERRORS OBSERVED=0.590000D+02

CHI-SQUARE= 22.9346
0.950 QUANTILE FOR CHI-SQUARE WITH 14 DEGREES OF FREEDOM= 23.6908

IBM POISSON

THE ESTIMATE OF PHI=0.489886D-01
NUMBER OF ITERATIONS= 5

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS= 63

TAU	OBS	EXPECTED(COND)	SD(COND)
2.00	3	6.02	2.45
1.00	0	3.03	1.74
6.00	14	15.34	3.92
1.00	0	2.64	1.63
3.00	7	6.71	2.59
5.00	18	9.76	3.12
1.00	2	1.42	1.19
1.00	0	0.98	0.99
2.00	5	1.81	1.35
4.00	3	2.72	1.65
5.00	3	2.21	1.49
1.00	0	0.44	0.66
1.00	0	0.39	0.62
13.00	3	3.33	1.82
3.00	0	0.69	0.83
4.00	1	0.72	0.85
1.00	0	0.14	0.38

CHI-SQUARE=0.232293D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 15 DEGREES OF FREEDOM= 24.9997

BINOMIAL

THE ESTIMATE OF N= 64
THE ESTIMATE OF A= 0.52080-01

TAU	OBS	EXPECTED(COND)	SD(COND)
2.00	3	6.38	2.53
1.00	0	3.12	1.77
6.00	14	16.50	4.06
1.00	0	2.41	1.55
3.00	7	6.87	2.62
5.00	18	9.28	3.05
1.00	2	1.14	1.07
1.00	0	1.04	1.02
2.00	5	2.03	1.42
4.00	3	2.91	1.71
5.00	3	2.86	1.69
1.00	0	0.48	0.69
1.00	0	0.48	0.69
13.00	3	4.67	2.16
3.00	0	0.94	0.97
4.00	1	1.22	1.11
1.00	0	0.28	0.53

CHI-SQUARE= 24.7596
0.950 QUANTILE FOR CHI-SQUARE WITH 15 DEGREES OF FREEDOM= 24.9997

IBM POISSON WITH VARIABLE ALPHA

APS DAZ SD

GEOMETRIC POISSON

THE ESTIMATE OF K=0.929014D+00
NUMBER OF ITERATIONS= 5

THE ESTIMATE OF LAMBDA=0.218890D+01

TAU	OBS	EXPECTED(COND)	SD(COND)
2.00	3	4.22	2.05
7.00	9	10.72	3.27
2.00	3	2.18	1.48
2.00	4	1.88	1.37
4.00	4	3.02	1.74
5.00	2	2.72	1.65
1.00	0	0.43	0.66
1.00	2	0.40	0.63
1.00	0	0.37	0.61
6.00	2	1.75	1.32
18.00	1	2.31	1.52

CHI-SQUARE=0.117709D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 9 DEGREES OF FREEDOM= 16.9252

JELINSKI-MORANDA

THE ESTIMATE OF N= 31
THE ESTIMATE OF ALPHA= 0.1000D+01
THE ESTIMATE OF PHI= 0.5205D-01
NUMBER OF ITERATIONS= 20

TAU	OBS	EXPECTED(COND)	SD(COND)
2.00	3	3.28	1.81
7.00	9	11.10	3.33
2.00	3	2.34	1.53
2.00	4	2.24	1.50
4.00	4	3.64	1.91
5.00	2	3.51	1.87
1.00	0	0.55	0.74
1.00	2	0.49	0.70
1.00	0	0.39	0.62
6.00	2	1.09	1.04
18.00	1	1.38	1.18

CHI-SQUARE= 9.0968
0.950 QUANTILE FOR CHI-SQUARE WITH 9 DEGREES OF FREEDOM= 16.9252

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= 31

THE ESTIMATE OF B= 0.7363D-01
NUMBER OF ITERATIONS= 2

TAU	OBS	EXPECTED(COND)	SD(COND)
2.00	3	4.22	2.05
7.00	9	10.72	3.27
2.00	3	2.18	1.48
2.00	4	1.88	1.37
4.00	4	3.02	1.74
5.00	2	2.72	1.65
1.00	0	0.43	0.66
1.00	2	0.40	0.63
1.00	0	0.37	0.61
6.00	2	1.75	1.32
18.00	1	2.31	1.52

CHI-SQUARE= 11.7709
0.950 QUANTILE FOR CHI-SQUARE WITH 9 DEGREES OF FREEDOM= 16.9252

GENERALIZED POISSON

THE ESTIMATE OF N= 33
THE ESTIMATE OF ALPHA= 0.6543D+00
THE ESTIMATE OF PHI= 0.7765D-01
NUMBER OF ITERATIONS= 6

TAU	OBS	EXPECTED(COND)	SD(COND)
2.00	3	3.98	1.99
7.00	9	8.75	2.96
2.00	3	2.88	1.70
2.00	4	2.76	1.66
4.00	4	3.57	1.89
5.00	2	3.24	1.80
1.00	0	0.90	0.95
1.00	2	0.82	0.90
1.00	0	0.66	0.81
6.00	2	1.14	1.07
18.00	1	1.31	1.14

THE CUMULATIVE NUMBER OF ERRORS OBSERVED=0.300000D+02

CHI-SQUARE= 5.3252
0.950 QUANTILE FOR CHI-SQUARE WITH 8 DEGREES OF FREEDOM= 15.5118

IBM POISSON

THE ESTIMATE OF PHI=0.733781D-01
NUMBER OF ITERATIONS= 4

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS= 29

TAU	OBS	EXPECTED(COND)	SD(COND)
2.00	3	4.09	2.02
7.00	9	11.55	3.40
2.00	3	2.82	1.68
2.00	4	2.68	1.64
4.00	4	3.92	1.98
5.00	2	3.46	1.86
1.00	0	0.58	0.76
1.00	2	0.51	0.71
1.00	0	0.36	0.60
6.00	2	0.34	0.58
18.00	1	-0.80	0.89

CHI-SQUARE=0.115022D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 9 DEGREES OF FREEDOM= 16.9252

BINOMIAL

THE ESTIMATE OF N= 32
THE ESTIMATE OF A= 0.6038D-01

TAU	OBS	EXPECTED(COND)	SD(COND)
2.00	3	3.59	1.89
7.00	9	9.83	3.14
2.00	3	2.22	1.49
2.00	4	1.88	1.37
4.00	4	2.69	1.64
5.00	2	2.22	1.49
1.00	0	0.38	0.62
1.00	2	0.38	0.62
1.00	0	0.27	0.51
6.00	2	1.38	1.17
18.00	1	1.67	1.29

CHI-SQUARE= 11.5401
0.950 QUANTILE FOR CHI-SQUARE WITH 9 DEGREES OF FREEDOM= 16.9252

IBM POISSON WITH VARIABLE ALPHA

APS DAZ ST

GEOMETRIC POISSON

THE ESTIMATE OF K=0.926852D+00
NUMBER OF ITERATIONS= 5

THE ESTIMATE OF LAMBDA=0.211883D+01

TAU	OBS	EXPECTED(COND)	SD(COND)
2.00	5	4.08	2.02

1.00	0	1.82	1.35
2.00	3	3.25	1.80
3.00	3	4.04	2.01
1.00	0	1.15	1.07
3.00	6	2.98	1.73
2.00	2	1.64	1.28
2.00	1	1.41	1.19
1.00	2	0.63	0.79
4.00	3	2.09	1.44
1.00	0	0.43	0.66
4.00	1	1.43	1.19
4.00	0	1.05	1.03

CHI-SQUARE=0.117299D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 11 DEGREES OF FREEDOM= 19.6806

JELINSKI-MORANDA

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= 29
THE ESTIMATE OF B= 0.7596D-01
NUMBER OF ITERATIONS= 2

TAU	OBS	EXPECTED(COND)	SD(COND)
2.00	5	4.08	2.02
1.00	0	1.82	1.35
2.00	3	3.25	1.80
3.00	3	4.04	2.01
1.00	0	1.15	1.07
3.00	6	2.98	1.73
2.00	2	1.64	1.28
2.00	1	1.41	1.19
1.00	2	0.63	0.79
4.00	3	2.09	1.44
1.00	0	0.43	0.66
4.00	1	1.43	1.19
4.00	0	1.05	1.03

CHI-SQUARE= 11.7299
0.950 QUANTILE FOR CHI-SQUARE WITH 11 DEGREES OF FREEDOM= 19.6806

GENERALIZED POISSON

IBM POISSON

THE ESTIMATE OF PHI=0.804047D-01
NUMBER OF ITERATIONS= 5

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS= 27

TAU	OBS	EXPECTED(COND)	SD(COND)
2.00	5	4.15	2.04
1.00	0	1.92	1.39
2.00	3	3.37	1.84
3.00	3	4.42	2.10
1.00	0	1.36	1.16
3.00	6	3.53	1.88
2.00	2	1.98	1.41
2.00	1	1.37	1.17
1.00	2	0.63	0.79
4.00	3	1.67	1.29
1.00	0	0.31	0.56
4.00	1	0.81	0.90
4.00	0	0.24	0.49

CHI-SQUARE=0.104038D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 11 DEGREES OF FREEDOM= 19.6806

BINOMIAL

THE ESTIMATE OF N= 29
THE ESTIMATE OF A= 0.7654D-01

TAU	OBS	EXPECTED(COND)	SD(COND)
2.00	5	4.18	2.05
1.00	0	1.80	1.34
2.00	3	3.47	1.86
3.00	3	4.40	2.10
1.00	0	1.36	1.17
3.00	6	3.79	1.95
2.00	2	1.77	1.33
2.00	1	1.49	1.22
1.00	2	0.70	0.84
4.00	3	1.97	1.40
1.00	0	0.33	0.57
4.00	1	1.18	1.09
4.00	0	0.91	0.96

CHI-SQUARE= 9.5557
0.950 QUANTILE FOR CHI-SQUARE WITH 11 DEGREES OF FREEDOM= 19.6806

IBM POISSON WITH VARIABLE ALPHA

APS DAZ IN

GEOMETRIC POISSON

THE ESTIMATE OF K=0.938641D+00
NUMBER OF ITERATIONS= 5

THE ESTIMATE OF LAMBDA=0.800517D+00

TAU	OBS	EXPECTED(COND)	SD(COND)
2.00	2	1.55	1.25
2.00	0	1.37	1.17
2.00	1	1.20	1.10
2.00	2	1.06	1.03
4.00	3	1.76	1.33
1.00	0	0.37	0.61
2.00	0	0.68	0.83

CHI-SQUARE=0.429288D+01
0.950 QUANTILE FOR CHI-SQUARE WITH 5 DEGREES OF FREEDOM= 11.0733

JELINSKI-MORANDA

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= 13
THE ESTIMATE OF B= 0.6332D-01
NUMBER OF ITERATIONS= 2

TAU	OBS	EXPECTED(COND)	SD(COND)
2.00	2	1.55	1.25
2.00	0	1.37	1.17
2.00	1	1.20	1.10
2.00	2	1.06	1.03
4.00	3	1.76	1.33
1.00	0	0.37	0.61
2.00	0	0.68	0.83

CHI-SQUARE= 4.2929
0.950 QUANTILE FOR CHI-SQUARE WITH 5 DEGREES OF FREEDOM= 11.0733

GENERALIZED POISSON

THE ESTIMATE OF N= 5
THE ESTIMATE OF ALPHA=-0.2271D+01
THE ESTIMATE OF PHI= 0.4781D+01
NUMBER OF ITERATIONS= 7

TAU	OBS	EXPECTED(COND)	SD(COND)
2.00	2	5.34	2.31
2.00	0	4.35	2.08
2.00	1	2.37	1.54
2.00	2	1.38	1.17
4.00	3	0.08	0.28
1.00	0	-2.92	1.71
2.00	0	-2.59	1.61

THE CUMULATIVE NUMBER OF ERRORS OBSERVED=0.800000D+01

CHI-SQUARE= 108.8003
0.950 QUANTILE FOR CHI-SQUARE WITH 4 DEGREES OF FREEDOM= 9.4917

IBM POISSON

THE ESTIMATE OF PHI=0.899843D-01
NUMBER OF ITERATIONS= 9

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS= 10

TAU	OBS	EXPECTED(COND)	SD(COND)
2.00	2	1.73	1.31
2.00	0	1.56	1.25
2.00	1	1.21	1.10
2.00	2	1.04	1.02
4.00	3	1.59	1.26
1.00	0	0.37	0.60
2.00	0	0.35	0.59

CHI-SQUARE=0.448997D+01
0.950 QUANTILE FOR CHI-SQUARE WITH 5 DEGREES OF FREEDOM= 11.0733

BINOMIAL

THE ESTIMATE OF N= 16
THE ESTIMATE OF A= 0.52340-01

TAU	OBS	EXPECTED(COND)	SD(COND)
2.00	2	1.60	1.26
2.00	0	1.40	1.18
2.00	1	1.40	1.18
2.00	2	1.30	1.14
4.00	3	2.10	1.45
1.00	0	0.41	0.64
2.00	0	0.80	0.90

CHI-SQUARE= 3.5982
0.950 QUANTILE FOR CHI-SQUARE WITH 5 DEGREES OF FREEDOM= 11.0733

IBM POISSON WITH VARIABLE ALPHA

APS SAD IT

GEOMETRIC POISSON

THE ESTIMATE OF K=0.938426D+00
NUMBER OF ITERATIONS= 5

THE ESTIMATE OF LAMBDA=0.316891D+01

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	6	3.17	1.78
1.00	8	2.97	1.72
1.00	1	2.79	1.67
3.00	4	7.38	2.72
7.00	4	12.62	3.55
5.00	6	6.13	2.48
2.00	3	1.96	1.40
2.00	2	1.72	1.31
2.00	7	1.52	1.23
3.00	4	1.94	1.39
2.00	2	1.10	1.05
1.00	0	0.50	0.71
1.00	1	0.47	0.69
20.00	1	5.16	2.27
5.00	1	0.55	0.74

CHI-SQUARE=0.477485D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 13 DEGREES OF FREEDOM= 22.3668

JELINSKI-MORANDA

THE ESTIMATE OF N= 51
THE ESTIMATE OF ALPHA= 0.1000D+01
THE ESTIMATE OF PHI= 0.5813D-01
NUMBER OF ITERATIONS= 3

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	6	2.99	1.73
1.00	8	2.88	1.70
1.00	1	2.24	1.50
3.00	4	6.36	2.52
7.00	4	12.81	3.58
5.00	6	8.28	2.88
2.00	3	2.73	1.65
2.00	2	2.27	1.51
2.00	7	2.15	1.47
3.00	4	2.35	1.53
2.00	2	0.99	0.99
1.00	0	0.44	0.66
1.00	1	0.20	0.45
20.00	1	2.89	1.70
5.00	1	0.43	0.66

CHI-SQUARE= 39.1583
0.950 QUANTILE FOR CHI-SQUARE WITH 13 DEGREES OF FREEDOM= 22.3668

NONHOMOGENEOUS POISSON

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THE ESTIMATE OF N=      51
THE ESTIMATE OF B= 0.6355D-01
NUMBER OF ITERATIONS=      2
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TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	6	3.17	1.78
1.00	8	2.97	1.72
1.00	1	2.79	1.67
3.00	4	7.38	2.72
7.00	4	12.62	3.55
5.00	6	6.13	2.48
2.00	3	1.96	1.40
2.00	2	1.72	1.31
2.00	7	1.52	1.23
3.00	4	1.94	1.39
2.00	2	1.10	1.05
1.00	0	0.50	0.71
1.00	1	0.47	0.69
20.00	1	5.16	2.27
5.00	1	0.55	0.74

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CHI-SQUARE=     47.7485
0.950 QUANTILE FOR CHI-SQUARE WITH  13 DEGREES OF FREEDOM=     22.3668
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GENERALIZED POISSON

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THE ESTIMATE OF N=      57
THE ESTIMATE OF ALPHA= 0.1874D+00
THE ESTIMATE OF PHI= 0.1044D+00
NUMBER OF ITERATIONS=      7
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TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	6	5.94	2.44
1.00	8	5.73	2.39
1.00	1	4.59	2.14
3.00	4	5.38	2.32
7.00	4	5.55	2.36
5.00	6	4.79	2.19
2.00	3	3.44	1.85
2.00	2	2.96	1.72
2.00	7	2.84	1.69
3.00	4	2.43	1.55
2.00	2	1.65	1.29
1.00	0	1.35	1.16
1.00	1	0.93	0.96
20.00	1	1.45	1.20
5.00	1	0.98	0.99

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THE CUMULATIVE NUMBER OF ERRORS OBSERVED=0.500000D+02

CHI-SQUARE=     13.8245
0.950 QUANTILE FOR CHI-SQUARE WITH  12 DEGREES OF FREEDOM=     21.0297
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IBM POISSON

THE ESTIMATE OF PHI=0.665775D-01
NUMBER OF ITERATIONS= 6

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS= 52

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	6	3.46	1.86
1.00	8	3.33	1.82
1.00	1	2.60	1.61
3.00	4	6.91	2.63
7.00	4	12.24	3.50
5.00	6	8.45	2.91
2.00	3	3.09	1.76
2.00	2	2.57	1.60
2.00	7	2.44	1.56
3.00	4	2.61	1.62
2.00	2	1.16	1.08
1.00	0	0.53	0.73
1.00	1	0.27	0.51
20.00	1	2.23	1.49
5.00	1	0.58	0.76

CHI-SQUARE=0.304158D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 13 DEGREES OF FREEDOM= 22.3668

BINOMIAL

THE ESTIMATE OF N= 51
THE ESTIMATE OF A= 0.4415D-01

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	6	2.20	1.48
1.00	8	1.94	1.39
1.00	1	1.60	1.26
3.00	4	4.47	2.11
7.00	4	8.51	2.92
5.00	6	5.55	2.36
2.00	3	1.86	1.36
2.00	2	1.61	1.27
2.00	7	1.44	1.20
3.00	4	1.24	1.11
2.00	2	0.51	0.71
1.00	0	0.17	0.42
1.00	1	0.17	0.42
20.00	1	1.76	1.33
5.00	1	0.40	0.63

CHI-SQUARE= 66.3159
0.950 QUANTILE FOR CHI-SQUARE WITH 13 DEGREES OF FREEDOM= 22.3668

IBM POISSON WITH VARIABLE ALPHA

APS SAD SD

GEOMETRIC POISSON

THE ESTIMATE OF K=0.907534D+00
NUMBER OF ITERATIONS= 5

THE ESTIMATE OF LAMBDA=0.483692D+01

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	3	4.84	2.20
2.00	6	8.37	2.89
1.00	0	3.62	1.90
1.00	6	3.28	1.81
1.00	2	2.98	1.73
1.00	2	2.70	1.64
4.00	16	8.53	2.92
2.00	6	3.17	1.78
2.00	4	2.61	1.62
3.00	1	3.08	1.76
3.00	1	2.30	1.52
1.00	0	0.63	0.79
1.00	1	0.57	0.76
1.00	1	0.52	0.72
6.00	1	2.25	1.50
8.00	1	1.54	1.24

CHI-SQUARE=0.219550D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 14 DEGREES OF FREEDOM= 23.6908

JELINSKI-MORANDA

THE ESTIMATE OF N= 53
THE ESTIMATE OF ALPHA= 0.1000D+01
THE ESTIMATE OF PHI= 0.7088D-01
NUMBER OF ITERATIONS= 10

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	3	3.74	1.93
2.00	6	7.34	2.71
1.00	0	3.60	1.90
1.00	6	3.39	1.84
1.00	2	3.32	1.82
1.00	2	3.17	1.78
4.00	16	10.71	3.27
2.00	6	3.51	1.87
2.00	4	3.09	1.76
3.00	1	3.14	1.77
3.00	1	2.50	1.58

1.00	0	0.55	0.74
1.00	1	0.41	0.64
1.00	1	0.34	0.58
6.00	1	1.18	1.09
8.00	1	1.01	1.00

CHI-SQUARE= 16.6943
0.950 QUANTILE FOR CHI-SQUARE WITH 14 DEGREES OF FREEDOM= 23.6908

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= 52
THE ESTIMATE OF B= 0.9702D-01
NUMBER OF ITERATIONS= 3

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	3	4.84	2.20
2.00	6	8.37	2.89
1.00	0	3.62	1.90
1.00	6	3.28	1.81
1.00	2	2.98	1.73
1.00	2	2.70	1.64
4.00	16	8.53	2.92
2.00	6	3.17	1.78
2.00	4	2.61	1.62
3.00	1	3.08	1.76
3.00	1	2.30	1.52
1.00	0	0.63	0.79
1.00	1	0.57	0.76
1.00	1	0.52	0.72
6.00	1	2.25	1.50
8.00	1	1.54	1.24

CHI-SQUARE= 21.9550
0.950 QUANTILE FOR CHI-SQUARE WITH 14 DEGREES OF FREEDOM= 23.6908

GENERALIZED POISSON

THE ESTIMATE OF N= 52
THE ESTIMATE OF ALPHA= 0.1300D+01
THE ESTIMATE OF PHI= 0.5928D-01
NUMBER OF ITERATIONS= 7

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	3	3.09	1.76
2.00	6	7.46	2.73
1.00	0	2.97	1.72
1.00	6	2.79	1.67
1.00	2	2.73	1.65
1.00	2	2.61	1.62
4.00	16	13.33	3.65

2.00	6	3.52	1.88
2.00	4	3.08	1.75
3.00	1	3.48	1.87
3.00	1	2.74	1.66
1.00	0	0.42	0.65
1.00	1	0.30	0.55
1.00	1	0.24	0.49
6.00	1	1.27	1.13
8.00	1	0.96	0.98

THE CUMULATIVE NUMBER OF ERRORS OBSERVED=0.510000D+02

CHI-SQUARE= 17.1907
0.950 QUANTILE FOR CHI-SQUARE WITH 13 DEGREES OF FREEDOM= 22.3668

IBM POISSON

THE ESTIMATE OF PHI=0.922529D-01
NUMBER OF ITERATIONS= 3

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS= 49

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	3	4.48	2.12
2.00	6	8.37	2.89
1.00	0	4.29	2.07
1.00	6	4.02	2.00
1.00	2	3.92	1.98
1.00	2	3.74	1.93
4.00	16	10.77	3.28
2.00	6	3.61	1.90
2.00	4	3.09	1.76
3.00	1	2.66	1.63
3.00	1	1.90	1.33
1.00	0	0.33	0.57
1.00	1	0.14	0.38
1.00	1	0.05	0.22
6.00	1	-0.65	0.80
8.00	1	-1.33	1.15

CHI-SQUARE=0.296504D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 14 DEGREES OF FREEDOM= 23.6908

BINOMIAL

THE ESTIMATE OF N= 53
THE ESTIMATE OF A= 0.9778D-01

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	3	4.96	2.23
2.00	6	8.92	2.99

1.00	0	4.12	2.03
1.00	6	4.12	2.03
1.00	2	3.56	1.89
1.00	2	3.37	1.84
4.00	16	11.07	3.33
2.00	6	3.23	1.80
2.00	4	2.17	1.47
3.00	1	2.08	1.44
3.00	1	1.83	1.35
1.00	0	0.58	0.76
1.00	1	0.58	0.76
1.00	1	0.48	0.70
6.00	1	1.86	1.36
8.00	1	1.73	1.32

CHI-SQUARE= 17.1500
0.950 QUANTILE FOR CHI-SQUARE WITH 14 DEGREES OF FREEDOM= 23.6908

IBM POISSON WITH VARIABLE ALPHA

APS SAD ST

GEOMETRIC POISSON

THE ESTIMATE OF K=0.928056D+00
NUMBER OF ITERATIONS= 5

THE ESTIMATE OF LAMBDA=0.169485D+01

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	0	1.69	1.30
1.00	3	1.57	1.25
1.00	0	1.46	1.21
3.00	7	3.78	1.94
4.00	2	3.89	1.97
5.00	3	3.48	1.87
3.00	4	1.54	1.24
2.00	0	0.85	0.92
2.00	0	0.73	0.86

CHI-SQUARE=0.136776D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 7 DEGREES OF FREEDOM= 14.0702

JELINSKI-MORANDA

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= 24
THE ESTIMATE OF B= 0.7466D-01
NUMBER OF ITERATIONS= 2

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	0	1.69	1.30
1.00	3	1.57	1.25
1.00	0	1.46	1.21
3.00	7	3.78	1.94
4.00	2	3.89	1.97
5.00	3	3.48	1.87
3.00	4	1.54	1.24
2.00	0	0.85	0.92
2.00	0	0.73	0.86

CHI-SQUARE= 13.6776
0.950 QUANTILE FOR CHI-SQUARE WITH 7 DEGREES OF FREEDOM= 14.0702

GENERALIZED POISSON

THE ESTIMATE OF N= 21
THE ESTIMATE OF ALPHA= 0.1314D+01
THE ESTIMATE OF PHI= 0.6396D-01
NUMBER OF ITERATIONS= 8

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	0	1.33	1.15
1.00	3	1.26	1.12
1.00	0	1.14	1.07
3.00	7	4.55	2.13
4.00	2	4.26	2.06
5.00	3	4.12	2.03
3.00	4	1.29	1.14
2.00	0	0.60	0.77
2.00	0	0.44	0.66

THE CUMULATIVE NUMBER OF ERRORS OBSERVED=0.190000D+02

CHI-SQUARE= 14.3756
0.950 QUANTILE FOR CHI-SQUARE WITH 6 DEGREES OF FREEDOM= 12.5961

IBM POISSON

THE ESTIMATE OF PHI=0.789144D-01
NUMBER OF ITERATIONS= 5

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS= 23

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	0	1.78	1.34
1.00	3	1.70	1.31
1.00	0	1.55	1.24
3.00	7	4.06	2.02
4.00	2	3.53	1.88

5.00	3	3.23	1.80
3.00	4	1.44	1.20
2.00	0	0.85	0.92
2.00	0	0.70	0.83

CHI-SQUARE=0.132103D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 7 DEGREES OF FREEDOM= 14.0702

BINOMIAL

THE ESTIMATE OF N= 21
THE ESTIMATE OF A= 0.1054D+00

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	0	2.08	1.44
1.00	3	2.08	1.44
1.00	0	1.78	1.33
3.00	7	4.82	2.19
4.00	2	3.71	1.93
5.00	3	3.59	1.90
3.00	4	1.57	1.25
2.00	0	0.34	0.58
2.00	0	0.34	0.58

CHI-SQUARE= 10.5990
0.950 QUANTILE FOR CHI-SQUARE WITH 7 DEGREES OF FREEDOM= 14.0702

IBM POISSON WITH VARIABLE ALPHA

APS SAD IN
APS ZBZ IT

GEOMETRIC POISSON

THE ESTIMATE OF K=0.938260D+00
NUMBER OF ITERATIONS= 5

THE ESTIMATE OF LAMBDA=0.131440D+01

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	0	1.31	1.15
5.00	2	5.45	2.33
10.00	13	6.85	2.62
1.00	2	0.47	0.69
3.00	1	1.25	1.12
1.00	0	0.37	0.61
3.00	0	0.97	0.99
6.00	1	1.47	1.21
14.00	1	1.86	1.36

CHI-SQUARE=0.158781D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 7 DEGREES OF FREEDOM= 14.0702

JELINSKI-MORANDA

THE ESTIMATE OF N= 21
THE ESTIMATE OF ALPHA= 0.1000D+01
THE ESTIMATE OF PHI= 0.5008D-01
NUMBER OF ITERATIONS= 5

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	0	1.07	1.04
5.00	2	5.11	2.26
10.00	13	9.72	3.12
1.00	2	0.62	0.79
3.00	1	0.96	0.98
1.00	0	0.27	0.52
3.00	0	0.51	0.72
6.00	1	0.73	0.85
14.00	1	0.99	1.00

CHI-SQUARE= 8.0144
0.950 QUANTILE FOR CHI-SQUARE WITH 7 DEGREES OF FREEDOM= 14.0702

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= 21
THE ESTIMATE OF B= 0.6373D-01
NUMBER OF ITERATIONS= 2

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	0	1.31	1.15
5.00	2	5.45	2.33
10.00	13	6.85	2.62
1.00	2	0.47	0.69
3.00	1	1.25	1.12
1.00	0	0.37	0.61
3.00	0	0.97	0.99
6.00	1	1.47	1.21
14.00	1	1.86	1.36

CHI-SQUARE= 15.8781
0.950 QUANTILE FOR CHI-SQUARE WITH 7 DEGREES OF FREEDOM= 14.0702

GENERALIZED POISSON

THE ESTIMATE OF N= 21
THE ESTIMATE OF ALPHA= 0.1284D+01
THE ESTIMATE OF PHI= 0.2995D-01
NUMBER OF ITERATIONS= 14

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	0	0.64	0.80
5.00	2	4.79	2.19
10.00	13	11.09	3.33
1.00	2	0.37	0.61
3.00	1	0.77	0.88
1.00	0	0.16	0.40
3.00	0	0.40	0.63
6.00	1	0.68	0.82
14.00	1	1.12	1.06

THE CUMULATIVE NUMBER OF ERRORS OBSERVED=0.200000D+02

CHI-SQUARE= 10.6501
0.950 QUANTILE FOR CHI-SQUARE WITH 6 DEGREES OF FREEDOM= 12.5961

IBM POISSON

THE ESTIMATE OF PHI=0.551559D-01
NUMBER OF ITERATIONS= 6

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS= 22

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	0	1.20	1.10
5.00	2	5.12	2.26
10.00	13	8.55	2.92
1.00	2	0.70	0.84
3.00	1	1.06	1.03
1.00	0	0.32	0.56
3.00	0	0.59	0.77
6.00	1	0.79	0.89
14.00	1	0.96	0.98

CHI-SQUARE=0.877386D+01
0.950 QUANTILE FOR CHI-SQUARE WITH 7 DEGREES OF FREEDOM= 14.0702

BINOMIAL

THE ESTIMATE OF N= 22
THE ESTIMATE OF A= 0.6602D-01

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	0	1.39	1.18
5.00	2	6.10	2.47
10.00	13	9.51	3.08
1.00	2	0.43	0.65
3.00	1	0.84	0.92
1.00	0	0.24	0.49

3.00	0	0.66	0.81
6.00	1	1.20	1.10
14.00	1	1.62	1.27

CHI-SQUARE= 12.4096
0.950 QUANTILE FOR CHI-SQUARE WITH 7 DEGREES OF FREEDOM= 14.0702

IBM POISSON WITH VARIABLE ALPHA

APS ZBZ SD

GEOMETRIC POISSON

THE ESTIMATE OF K=0.940924D+00
NUMBER OF ITERATIONS= 4

THE ESTIMATE OF LAMBDA=0.511472D+01

TAU	OBS	EXPECTED(COND)	SD(COND)
3.00	1	14.46	3.80
6.00	26	22.07	4.70
1.00	4	2.96	1.72
1.00	6	2.78	1.67
2.00	10	5.08	2.25
4.00	13	8.48	2.91
2.00	4	3.53	1.88
1.00	4	1.61	1.27
2.00	4	2.94	1.71
1.00	0	1.34	1.16
1.00	2	1.26	1.12
1.00	1	1.19	1.09
1.00	1	1.12	1.06
5.00	1	4.67	2.16
6.00	2	4.01	2.00
3.00	0	1.52	1.23

CHI-SQUARE=0.357130D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 14 DEGREES OF FREEDOM= 23.6908

JELINSKI-MORANDA

THE ESTIMATE OF N= 85
THE ESTIMATE OF ALPHA= 0.1000D+01
THE ESTIMATE OF PHI= 0.5197D-01
NUMBER OF ITERATIONS= 10

TAU	OBS	EXPECTED(COND)	SD(COND)
3.00	1	13.31	3.65
6.00	26	26.00	5.10
1.00	4	4.23	2.06
1.00	6	3.61	1.90
2.00	10	7.00	2.65

4.00	13	10.26	3.20
2.00	4	2.95	1.72
1.00	4	1.21	1.10
2.00	4	2.33	1.53
1.00	0	0.75	0.86
1.00	2	0.70	0.83
1.00	1	0.64	0.80
1.00	1	0.54	0.73
5.00	1	2.18	1.48
6.00	2	2.30	1.52
3.00	0	0.99	1.00

CHI-SQUARE= 28.4206
0.950 QUANTILE FOR CHI-SQUARE WITH 14 DEGREES OF FREEDOM= 23.6908

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= 87
THE ESTIMATE OF B= 0.6089D-01
NUMBER OF ITERATIONS= 2

TAU	OBS	EXPECTED(COND)	SD(COND)
3.00	1	14.46	3.80
6.00	26	22.07	4.70
1.00	4	2.96	1.72
1.00	6	2.78	1.67
2.00	10	5.08	2.25
4.00	13	8.48	2.91
2.00	4	3.53	1.88
1.00	4	1.61	1.27
2.00	4	2.94	1.71
1.00	0	1.34	1.16
1.00	2	1.26	1.12
1.00	1	1.19	1.09
1.00	1	1.12	1.06
5.00	1	4.67	2.16
6.00	2	4.01	2.00
3.00	0	1.52	1.23

CHI-SQUARE= 35.7130
0.950 QUANTILE FOR CHI-SQUARE WITH 14 DEGREES OF FREEDOM= 23.6908

GENERALIZED POISSON

THE ESTIMATE OF N= 85
THE ESTIMATE OF ALPHA= 0.7128D+00
THE ESTIMATE OF PHI= 0.7220D-01
NUMBER OF ITERATIONS= 5

TAU	OBS	EXPECTED(COND)	SD(COND)
3.00	1	13.44	3.67

6.00	26	21.51	4.64
1.00	4	5.85	2.42
1.00	6	4.99	2.23
2.00	10	7.94	2.82
4.00	13	9.51	3.08
2.00	4	3.32	1.82
1.00	4	1.66	1.29
2.00	4	2.61	1.62
1.00	0	1.01	1.01
1.00	2	0.94	0.97
1.00	1	0.87	0.93
1.00	1	0.73	0.85
5.00	1	1.83	1.35
6.00	2	1.83	1.35
3.00	0	0.96	0.98

THE CUMULATIVE NUMBER OF ERRORS OBSERVED=0.790000D+02

CHI-SQUARE= 22.8874
0.950 QUANTILE FOR CHI-SQUARE WITH 13 DEGREES OF FREEDOM= 22.3668

IBM POISSON

THE ESTIMATE OF PHI=0.567742D-01
NUMBER OF ITERATIONS= 4

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS= 85

TAU	OBS	EXPECTED(COND)	SD(COND)
3.00	1	13.70	3.70
6.00	26	24.60	4.96
1.00	4	4.61	2.15
1.00	6	3.93	1.98
2.00	10	7.41	2.72
4.00	13	10.25	3.20
2.00	4	3.11	1.76
1.00	4	1.31	1.15
2.00	4	2.44	1.56
1.00	0	0.80	0.90
1.00	2	0.75	0.86
1.00	1	0.69	0.83
1.00	1	0.58	0.76
5.00	1	2.07	1.44
6.00	2	2.12	1.45
3.00	0	0.99	0.99

CHI-SQUARE=0.263029D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 14 DEGREES OF FREEDOM= 23.6908

BINOMIAL

THE ESTIMATE OF N= 93
THE ESTIMATE OF A= 0.4762D-01

TAU	OBS	EXPECTED(COND)	SD(COND)
3.00	1	12.32	3.51
6.00	26	22.74	4.77
1.00	4	3.05	1.75
1.00	6	2.86	1.69
2.00	10	5.04	2.25
4.00	13	7.89	2.81
2.00	4	2.95	1.72
1.00	4	1.33	1.15
2.00	4	2.23	1.49
1.00	0	0.95	0.98
1.00	2	0.95	0.98
1.00	1	0.86	0.93
1.00	1	0.81	0.90
5.00	1	3.50	1.87
6.00	2	3.85	1.96
3.00	0	1.80	1.34

CHI-SQUARE= 36.6033
0.950 QUANTILE FOR CHI-SQUARE WITH 14 DEGREES OF FREEDOM= 23.6908

IBM POISSON WITH VARIABLE ALPHA

APS ZBZ ST

GEOMETRIC POISSON

THE ESTIMATE OF K=0.927748D+00
NUMBER OF ITERATIONS= 5

THE ESTIMATE OF LAMBDA=0.341288D+01

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	3	3.41	1.85
1.00	1	3.17	1.78
1.00	2	2.94	1.71
1.00	2	2.73	1.65
2.00	5	4.87	2.21
3.00	11	6.07	2.46
1.00	2	1.74	1.32
1.00	5	1.61	1.27
4.00	0	5.37	2.32
3.00	4	3.09	1.76
4.00	6	3.17	1.78
5.00	0	2.84	1.68

CHI-SQUARE=0.241808D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 10 DEGREES OF FREEDOM= 18.3111

JELINSKI-MORANDA

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= 47
THE ESTIMATE OF B= 0.7500D-01
NUMBER OF ITERATIONS= 2

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	3	3.41	1.85
1.00	1	3.17	1.78
1.00	2	2.94	1.71
1.00	2	2.73	1.65
2.00	5	4.87	2.21
3.00	11	6.07	2.46
1.00	2	1.74	1.32
1.00	5	1.61	1.27
4.00	0	5.37	2.32
3.00	4	3.09	1.76
4.00	6	3.17	1.78
5.00	0	2.84	1.68

CHI-SQUARE= 24.1808
0.950 QUANTILE FOR CHI-SQUARE WITH 10 DEGREES OF FREEDOM= 18.3111

GENERALIZED POISSON

IBM POISSON

THE ESTIMATE OF PHI=0.803159D-01
NUMBER OF ITERATIONS= 5

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS= 44

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	3	3.57	1.89
1.00	1	3.32	1.82
1.00	2	3.24	1.80
1.00	2	3.16	1.78
2.00	5	5.77	2.40
3.00	11	7.20	2.68
1.00	2	1.72	1.31
1.00	5	1.48	1.22
4.00	0	4.95	2.23
3.00	4	2.75	1.66
4.00	6	2.67	1.64
5.00	0	1.16	1.08

CHI-SQUARE=0.239890D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 10 DEGREES OF FREEDOM= 18.3111

BINOMIAL

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THE ESTIMATE OF N=      45
THE ESTIMATE OF A= 0.8733D-01
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TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	3	3.74	1.93
1.00	1	3.49	1.87
1.00	2	3.40	1.84
1.00	2	3.24	1.80
2.00	5	5.88	2.42
3.00	11	7.30	2.70
1.00	2	1.73	1.32
1.00	5	1.56	1.25
4.00	0	4.04	2.01
3.00	4	3.16	1.78
4.00	6	2.86	1.69
5.00	0	1.31	1.14

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CHI-SQUARE=    21.5964
0.950 QUANTILE FOR CHI-SQUARE WITH  10 DEGREES OF FREEDOM=     18.3111
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IBM POISSON WITH VARIABLE ALPHA

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GEOMETRIC POISSON

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THE ESTIMATE OF K=0.970136D+00
NUMBER OF ITERATIONS=  5

THE ESTIMATE OF LAMBDA=0.642008D+00
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TAU	OBS	EXPECTED(COND)	SD(COND)
4.00	1	2.46	1.57
7.00	1	3.64	1.91
4.00	1	1.76	1.33
7.00	11	2.61	1.62
2.00	0	0.65	0.81
3.00	1	0.90	0.95
10.00	1	2.48	1.57
8.00	0	1.51	1.23
9.00	1	1.31	1.15
11.00	2	1.19	1.09
6.00	0	0.50	0.71

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CHI-SQUARE=0.342803D+02
0.950 QUANTILE FOR CHI-SQUARE WITH   9 DEGREES OF FREEDOM=     16.9252
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JELINSKI-MORANDA

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= 21
THE ESTIMATE OF B= 0.3032D-01
NUMBER OF ITERATIONS= 2

TAU	OBS	EXPECTED(COND)	SD(COND)
4.00	1	2.46	1.57
7.00	1	3.64	1.91
4.00	1	1.76	1.33
7.00	11	2.61	1.62
2.00	0	0.65	0.81
3.00	1	0.90	0.95
10.00	1	2.48	1.57
8.00	0	1.51	1.23
9.00	1	1.31	1.15
11.00	2	1.19	1.09
6.00	0	0.50	0.71

CHI-SQUARE= 34.2603
0.950 QUANTILE FOR CHI-SQUARE WITH 9 DEGREES OF FREEDOM= 16.9252

GENERALIZED POISSON

IBM POISSON

THE ESTIMATE OF PHI=0.3067540-01
NUMBER OF ITERATIONS= 4

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS= 21

TAU	OBS	EXPECTED(COND)	SD(COND)
4.00	1	2.46	1.57
7.00	1	3.71	1.93
4.00	1	2.10	1.45
7.00	11	3.32	1.82
2.00	0	0.96	0.98
3.00	1	1.33	1.16
10.00	1	1.59	1.26
8.00	0	1.09	1.05
9.00	1	0.97	0.98
11.00	2	0.86	0.93
6.00	0	0.33	0.58

CHI-SQUARE=0.253871D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 9 DEGREES OF FREEDOM= 16.9252

BINOMIAL

THE ESTIMATE OF N= 20
THE ESTIMATE OF A= 0.3911D-01

TAU	OBS	EXPECTED(COND)	SD(COND)
4.00	1	2.91	1.71
7.00	1	4.57	2.14
4.00	1	2.62	1.62
7.00	11	4.09	2.02
2.00	0	0.46	0.68
3.00	1	0.67	0.82
10.00	1	1.64	1.28
8.00	0	1.10	1.05
9.00	1	1.21	1.10
11.00	2	1.08	1.04
6.00	0	0.23	0.48

CHI-SQUARE= 19.7285
0.950 QUANTILE FOR CHI-SQUARE WITH 9 DEGREES OF FREEDOM= 16.9252

IBM POISSON WITH VARIABLE ALPHA

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GEOMETRIC POISSON

THE ESTIMATE OF K=0.871429D+00
NUMBER OF ITERATIONS= 5

THE ESTIMATE OF LAMBDA=0.350396D+01

TAU	OBS	EXPECTED(COND)	SD(COND)
2.00	10	6.56	2.56
1.00	1	2.66	1.63
1.00	1	2.32	1.52
6.00	10	8.83	2.97
2.00	1	1.66	1.29
7.00	1	3.23	1.80
3.00	0	0.67	0.82
4.00	1	0.56	0.75
5.00	2	0.38	0.62
2.00	0	0.09	0.30
1.00	0	0.04	0.19

CHI-SQUARE=0.136447D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 9 DEGREES OF FREEDOM= 16.9252

JELINSKI-MORANDA

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N=   27
THE ESTIMATE OF B= 0.1376D+00
NUMBER OF ITERATIONS=   3

TAU	OBS	EXPECTED(COND)	SD(COND)
2.00	10	6.56	2.56
1.00	1	2.66	1.63
1.00	1	2.32	1.52
6.00	10	8.83	2.97
2.00	1	1.66	1.29
7.00	1	3.23	1.80
3.00	0	0.67	0.82
4.00	1	0.56	0.75
5.00	2	0.38	0.62
2.00	0	0.09	0.30
1.00	0	0.04	0.19

CHI-SQUARE=   13.6447
0.950 QUANTILE FOR CHI-SQUARE WITH   9 DEGREES OF FREEDOM=   16.9252

GENERALIZED POISSON

IBM POISSON

THE ESTIMATE OF PHI=0.133390D+00
NUMBER OF ITERATIONS=   4

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS=   24

TAU	OBS	EXPECTED(COND)	SD(COND)
2.00	10	6.05	2.46
1.00	1	3.11	1.76
1.00	1	2.98	1.72
6.00	10	7.09	2.66
2.00	1	1.82	1.35
7.00	1	2.72	1.65
3.00	0	1.15	1.07
4.00	1	1.00	1.00
5.00	2	0.66	0.82
2.00	0	0.07	0.27
1.00	0	-0.36	0.60

CHI-SQUARE=0.115186D+02
0.950 QUANTILE FOR CHI-SQUARE WITH   9 DEGREES OF FREEDOM=   16.9252

BINOMIAL

THE ESTIMATE OF N= 26
THE ESTIMATE OF A= 0.2064D+00

TAU	OBS	EXPECTED(COND)	SD(COND)
2.00	10	8.68	2.95
1.00	1	2.92	1.71
1.00	1	2.73	1.65
6.00	10	9.70	3.11
2.00	1	1.24	1.11
7.00	1	2.03	1.43
3.00	0	0.77	0.88
4.00	1	0.93	0.97
5.00	2	0.43	0.65
2.00	0	-0.45	0.67
1.00	0	-0.25	0.50

CHI-SQUARE= 9.0205
0.950 QUANTILE FOR CHI-SQUARE WITH 9 DEGREES OF FREEDOM= 16.9252

IBM POISSON WITH VARIABLE ALPHA

OSS LDR ST

GEOMETRIC POISSON

THE ESTIMATE OF K=0.100418D+01
NUMBER OF ITERATIONS= 5

THE ESTIMATE OF LAMBDA=0.313582D+00

TAU	OBS	EXPECTED(COND)	SD(COND)
5.00	2	1.58	1.26
4.00	1	1.29	1.14
5.00	1	1.64	1.28
3.00	1	1.00	1.00
2.00	1	0.67	0.82
1.00	0	0.34	0.58
8.00	4	2.77	1.66
2.00	0	0.71	0.84

CHI-SQUARE=0.217857D+01
0.950 QUANTILE FOR CHI-SQUARE WITH 6 DEGREES OF FREEDOM= 12.5961

JELINSKI-MORANDA

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= -74
THE ESTIMATE OF B=-0.4168D-02
NUMBER OF ITERATIONS= 2

TAU	OBS	EXPECTED(COND)	SD(COND)
5.00	2	1.58	1.26
4.00	1	1.29	1.14
5.00	1	1.64	1.28
3.00	1	1.00	1.00
2.00	1	0.67	0.82
1.00	0	0.34	0.58
8.00	4	2.77	1.66
2.00	0	0.71	0.84

CHI-SQUARE=   2.1786
0.950 QUANTILE FOR CHI-SQUARE WITH   6 DEGREES OF FREEDOM=   12.5961

GENERALIZED POISSON

IBM POISSON

THE ESTIMATE OF PHI=0.721501D-04
NUMBER OF ITERATIONS= 10

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS=   2762

TAU	OBS	EXPECTED(COND)	SD(COND)
5.00	2	1.67	1.29
4.00	1	1.33	1.16
5.00	1	1.67	1.29
3.00	1	1.00	1.00
2.00	1	0.67	0.82
1.00	0	0.33	0.58
8.00	4	2.66	1.63
2.00	0	0.67	0.82

CHI-SQUARE=0.225292D+01
0.950 QUANTILE FOR CHI-SQUARE WITH   6 DEGREES OF FREEDOM=   12.5961

BINOMIAL

THE ESTIMATE OF N=   -15
THE ESTIMATE OF A=-0.1768D-01

TAU	OBS	EXPECTED(COND)	SD(COND)
5.00	2	1.51	1.23
4.00	1	1.34	1.16
5.00	1	1.79	1.34
3.00	1	1.11	1.05
2.00	1	0.77	0.88
1.00	0	0.40	0.63
8.00	4	3.40	1.84

2.00	0	0.95	0.97

CHI-SQUARE= 2.1291
0.950 QUANTILE FOR CHI-SQUARE WITH 6 DEGREES OF FREEDOM= 12.5961

IBM POISSON WITH VARIABLE ALPHA

SES VAS IT

GEOMETRIC POISSON

THE ESTIMATE OF K=0.969202D+00
NUMBER OF ITERATIONS= 4

THE ESTIMATE OF LAMBDA=0.611453D+00

TAU	OBS	EXPECTED(COND)	SD(COND)
7.00	3	3.90	1.98
1.00	0	0.49	0.70
7.00	3	3.04	1.74
2.00	2	0.75	0.87
1.00	0	0.36	0.60
1.00	1	0.35	0.59
1.00	0	0.34	0.58
4.00	4	1.25	1.12
4.00	0	1.10	1.05
6.00	0	1.42	1.19

CHI-SQUARE=0.132579D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 8 DEGREES OF FREEDOM= 15.5118

JELINSKI-MORANDA

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= 20
THE ESTIMATE OF B= 0.3128D-01
NUMBER OF ITERATIONS= 2

TAU	OBS	EXPECTED(COND)	SD(COND)
7.00	3	3.90	1.98
1.00	0	0.49	0.70
7.00	3	3.04	1.74
2.00	2	0.75	0.87
1.00	0	0.36	0.60
1.00	1	0.35	0.59
1.00	0	0.34	0.58
4.00	4	1.25	1.12
4.00	0	1.10	1.05
6.00	0	1.42	1.19

CHI-SQUARE= 13.2579
0.950 QUANTILE FOR CHI-SQUARE WITH 8 DEGREES OF FREEDOM= 15.5118

GENERALIZED POISSON

IBM POISSON

THE ESTIMATE OF PHI=0.348362D-04
NUMBER OF ITERATIONS= 7

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS= 5231

TAU	OBS	EXPECTED(COND)	SD(COND)
7.00	3	2.68	1.64
1.00	0	0.38	0.62
7.00	3	2.68	1.64
2.00	2	0.77	0.87
1.00	0	0.38	0.62
1.00	1	0.38	0.62
1.00	0	0.38	0.62
4.00	4	1.53	1.24
4.00	0	1.53	1.24
6.00	0	2.29	1.51

CHI-SQUARE=0.120299D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 8 DEGREES OF FREEDOM= 15.5118

BINOMIAL

THE ESTIMATE OF N= 19
THE ESTIMATE OF A= 0.3132D-01

TAU	OBS	EXPECTED(COND)	SD(COND)
7.00	3	3.68	1.92
1.00	0	0.48	0.70
7.00	3	3.09	1.76
2.00	2	0.77	0.88
1.00	0	0.33	0.57
1.00	1	0.33	0.57
1.00	0	0.30	0.55
4.00	4	1.14	1.07
4.00	0	0.67	0.82
6.00	0	0.98	0.99

CHI-SQUARE= 13.3687
0.950 QUANTILE FOR CHI-SQUARE WITH 8 DEGREES OF FREEDOM= 15.5118

IBM POISSON WITH VARIABLE ALPHA

SES VAS SD

GEOMETRIC POISSON

THE ESTIMATE OF K=0.101080D+01
NUMBER OF ITERATIONS= 5

THE ESTIMATE OF LAMBDA=0.449589D+00

TAU	OBS	EXPECTED(COND)	SD(COND)
2.00	0	0.90	0.95
6.00	4	2.83	1.68
1.00	0	0.49	0.70
1.00	1	0.50	0.70
6.00	0	3.09	1.76
3.00	5	1.62	1.27
2.00	1	1.11	1.05
4.00	1	2.29	1.51
4.00	6	2.39	1.55
4.00	1	2.50	1.58
2.00	0	1.29	1.14

CHI-SQUARE=0.209073D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 9 DEGREES OF FREEDOM= 16.9252

JELINSKI-MORANDA

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= -41
THE ESTIMATE OF B=-0.1074D-01
NUMBER OF ITERATIONS= 3

TAU	OBS	EXPECTED(COND)	SD(COND)
2.00	0	0.90	0.95
6.00	4	2.83	1.68
1.00	0	0.49	0.70
1.00	1	0.50	0.70
6.00	0	3.09	1.76
3.00	5	1.62	1.27
2.00	1	1.11	1.05
4.00	1	2.29	1.51
4.00	6	2.39	1.55
4.00	1	2.50	1.58
2.00	0	1.29	1.14

CHI-SQUARE= 20.9073
0.950 QUANTILE FOR CHI-SQUARE WITH 9 DEGREES OF FREEDOM= 16.9[illegible]2

GENERALIZED POISSON

IBM POISSON

THE ESTIMATE OF PHI=0.128411D-03
NUMBER OF ITERATIONS= 12

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS= 3268

TAU	OBS	EXPECTED(COND)	SD(COND)
2.00	0	1.09	1.04
6.00	4	3.26	1.81
1.00	0	0.54	0.74
1.00	1	0.54	0.74
6.00	0	3.26	1.81
3.00	5	1.63	1.28
2.00	1	1.09	1.04
4.00	1	2.17	1.47
4.00	6	2.17	1.47
4.00	1	2.16	1.47
2.00	0	1.08	1.04

CHI-SQUARE=0.215292D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 9 DEGREES OF FREEDOM= 16.9252

BINOMIAL

IBM POISSON WITH VARIABLE ALPHA

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GEOMETRIC POISSON

THE ESTIMATE OF K=0.699858D+00
NUMBER OF ITERATIONS= 4

THE ESTIMATE OF LAMBDA=0.120874D+01

TAU	OBS	EXPECTED(COND)	SD(COND)
3.00	2	2.65	1.63
1.00	1	0.41	0.64
2.00	1	0.49	0.70
8.00	0	0.45	0.67

CHI-SQUARE=0.195342D+01
0.950 QUANTILE FOR CHI-SQUARE WITH 2 DEGREES OF FREEDOM= 5.9948

JELINSKI-MORANDA

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= 4
THE ESTIMATE OF B= 0.3569D+00
NUMBER OF ITERATIONS= 4

TAU	OBS	EXPECTED(COND)	SD(COND)
3.00	2	2.65	1.63
1.00	1	0.41	0.64
2.00	1	0.49	0.70
8.00	0	0.45	0.67

CHI-SQUARE= 1.9534
0.950 QUANTILE FOR CHI-SQUARE WITH 2 DEGREES OF FREEDOM= 5.9948

GENERALIZED POISSON

IBM POISSON

THE ESTIMATE OF PHI=0.424290D+00
NUMBER OF ITERATIONS= 17

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS= 4

TAU	OBS	EXPECTED(COND)	SD(COND)
3.00	2	2.85	1.69
1.00	1	1.07	1.03
2.00	1	0.35	0.59
8.00	0	-0.47	0.69

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GEOMETRIC POISSON

THE ESTIMATE OF K=0.103240D+01
NUMBER OF ITERATIONS= 6

THE ESTIMATE OF LAMBDA=0.216154D-01

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	1	0.02	0.15
3.00	1	0.07	0.26
4.00	0	0.10	0.32
63.00	3	5.56	2.36
8.00	3	1.87	1.37
6.00	0	1.75	1.32
12.00	1	4.68	2.16
7.00	5	3.68	1.92

3.00	1	1.85	1.36
1.00	1	0.66	0.81
2.00	6	1.38	1.17
3.00	6	2.24	1.50
1.00	1	0.79	0.89
1.00	0	0.82	0.91
4.00	0	3.55	1.88

CHI-SQUARE=0.907788D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 13 DEGREES OF FREEDOM= 22.3668

JELINSKI-MORANDA

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= 0
THE ESTIMATE OF B=-0.3189D-01
NUMBER OF ITERATIONS= 4

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	1	0.02	0.15
3.00	1	0.07	0.26
4.00	0	0.10	0.32
63.00	3	5.56	2.36
8.00	3	1.87	1.37
6.00	0	1.75	1.32
12.00	1	4.68	2.16
7.00	5	3.68	1.92
3.00	1	1.85	1.36
1.00	1	0.66	0.81
2.00	6	1.38	1.17
3.00	6	2.24	1.50
1.00	1	0.79	0.89
1.00	0	0.82	0.91
4.00	0	3.55	1.88

CHI-SQUARE= 90.7788
0.950 QUANTILE FOR CHI-SQUARE WITH 13 DEGREES OF FREEDOM= 22.3668

GENERALIZED POISSON

IBM POISSON

THE ESTIMATE OF PHI=0.367442D-04
NUMBER OF ITERATIONS= 9

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS= 3269

TAU	OBS	EXPECTED(COND)	SD(COND)

1.00	1	0.24	0.49
3.00	1	0.73	0.86
4.00	0	0.98	0.99
63.00	3	15.37	3.92
8.00	3	1.95	1.40
6.00	0	1.47	1.21
12.00	1	2.93	1.71
7.00	5	1.71	1.31
3.00	1	0.73	0.86
1.00	1	0.24	0.49
2.00	6	0.49	0.70
3.00	6	0.73	0.85
1.00	1	0.24	0.49
1.00	0	0.24	0.49
4.00	0	0.97	0.98

CHI-SQUARE=0.129444D+03
0.950 QUANTILE FOR CHI-SQUARE WITH 13 DEGREES OF FREEDOM= 22.3668

BINOMIAL

THE ESTIMATE OF N= 5
THE ESTIMATE OF A=-0.1340D-10

TAU	OBS	EXPECTED(COND)	SD(COND)
1.00	1	-0.00	0.00
3.00	1	-0.00	0.00
4.00	0	-0.00	0.00
63.00	3	-0.00	0.00
8.00	3	-0.00	0.00
6.00	0	0.00	0.00
12.00	1	0.00	0.00
7.00	5	0.00	0.00
3.00	1	0.00	0.00
1.00	1	0.00	0.00
2.00	6	0.00	0.00
3.00	6	0.00	0.00
1.00	1	0.00	0.00
1.00	0	0.00	0.00
4.00	0	0.00	0.00

CHI-SQUARE=***********
0.950 QUANTILE FOR CHI-SQUARE WITH 13 DEGREES OF FREEDOM= 22.3668

IBM POISSON WITH VARIABLE ALPHA

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GEOMETRIC POISSON

THE ESTIMATE OF K=0.102716D+01
NUMBER OF ITERATIONS= 5

THE ESTIMATE OF LAMBDA=0.284659D+00

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HUGHES AIRCRAFT CO FULLERTON CA GROUND SYSTEMS GROUP
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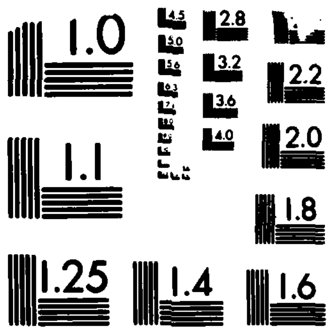

MICROCOPY RESOLUTION TEST CHART
NATIONAL BUREAU OF STANDARDS-1963-A

TAU	OBS	EXPECTED(COND)	SD(COND)
12.00	3	3.98	1.99
5.00	4	2.07	1.44
1.00	0	0.45	0.67
5.00	3	2.43	1.56
2.00	0	1.07	1.03

CHI-SQUARE=0.368053D+01
0.950 QUANTILE FOR CHI-SQUARE WITH 3 DEGREES OF FREEDOM= 7.8167

JELINSKI-MORANDA

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= -9
THE ESTIMATE OF B=-0.2680D-01
NUMBER OF ITERATIONS= 3

TAU	OBS	EXPECTED(COND)	SD(COND)
12.00	3	3.98	1.99
5.00	4	2.07	1.44
1.00	0	0.45	0.67
5.00	3	2.43	1.56
2.00	0	1.07	1.03

CHI-SQUARE= 3.6805
0.950 QUANTILE FOR CHI-SQUARE WITH 3 DEGREES OF FREEDOM= 7.8167

GENERALIZED POISSON

THE ESTIMATE OF N= 84
THE ESTIMATE OF ALPHA= 0.9162D+00
THE ESTIMATE OF PHI= 0.5767D-02
NUMBER OF ITERATIONS= 15

TAU	OBS	EXPECTED(COND)	SD(COND)
12.00	3	4.71	2.17
5.00	4	2.09	1.44
1.00	0	0.47	0.69
5.00	3	1.93	1.39
2.00	0	0.80	0.90

THE CUMULATIVE NUMBER OF ERRORS OBSERVED=0.100000D+02

CHI-SQUARE= 4.2390
0.950 QUANTILE FOR CHI-SQUARE WITH 2 DEGREES OF FREEDOM= 5.9948

IBM POISSON

THE ESTIMATE OF PHI=0.113169D-01
NUMBER OF ITERATIONS= 4

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS= 39

TAU	OBS	EXPECTED(COND)	SD(COND)
12.00	3	5.04	2.25
5.00	4	2.13	1.46
1.00	0	0.42	0.65
5.00	3	1.80	1.34
2.00	0	0.66	0.81

CHI-SQUARE=0.436152D+01
0.950 QUANTILE FOR CHI-SQUARE WITH 3 DEGREES OF FREEDOM= 7.8167

BINOMIAL

THE ESTIMATE OF N= 2
THE ESTIMATE OF A= 0.26490-15

TAU	OBS	EXPECTED(COND)	SD(COND)
12.00	3	0.00	0.00
5.00	4	-0.00	0.00
1.00	0	-0.00	0.00
5.00	3	-0.00	0.00
2.00	0	-0.00	0.00

CHI-SQUARE=***********
0.950 QUANTILE FOR CHI-SQUARE WITH 3 DEGREES OF FREEDOM= 7.8167

IBM POISSON WITH VARIABLE ALPHA

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GEOMETRIC POISSON

THE ESTIMATE OF K=0.949698D+00
NUMBER OF ITERATIONS= 5

THE ESTIMATE OF LAMBDA=0.604041D+00

TAU	OBS	EXPECTED(COND)	SD(COND)
4.00	0	2.24	1.50
5.00	5	2.22	1.49
5.00	0	1.72	1.31

3.00	1	0.84	0.91
2.00	0	0.49	0.70
1.00	2	0.23	0.48
1.00	1	0.22	0.46
1.00	0	0.20	0.45
16.00	2	2.17	1.47
10.00	0	0.68	0.83

CHI-SQUARE=0.255949D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 8 DEGREES OF FREEDOM= 15.5118

JELINSKI-MORANDA

THE ESTIMATE OF N= 12
THE ESTIMATE OF ALPHA= 0.1000D+01
THE ESTIMATE OF PHI= 0.4471D-01
NUMBER OF ITERATIONS= 5

TAU	OBS	EXPECTED(COND)	SD(COND)
4.00	0	2.17	1.47
5.00	5	2.49	1.58
5.00	0	2.04	1.43
3.00	1	1.09	1.04
2.00	0	0.64	0.80
1.00	2	0.23	0.48
1.00	1	0.18	0.43
1.00	0	0.14	0.37
16.00	2	1.52	1.23
10.00	0	0.50	0.71

CHI-SQUARE= 25.4756
0.950 QUANTILE FOR CHI-SQUARE WITH 8 DEGREES OF FREEDOM= 15.5118

NONHOMOGENEOUS POISSON

THE ESTIMATE OF N= 12
THE ESTIMATE OF B= 0.5161D-01
NUMBER OF ITERATIONS= 2

TAU	OBS	EXPECTED(COND)	SD(COND)
4.00	0	2.24	1.50
5.00	5	2.22	1.49
5.00	0	1.72	1.31
3.00	1	0.84	0.91
2.00	0	0.49	0.70
1.00	2	0.23	0.48
1.00	1	0.22	0.46
1.00	0	0.20	0.45
16.00	2	2.17	1.47
10.00	0	0.68	0.83

CHI-SQUARE= 25.5949
0.950 QUANTILE FOR CHI-SQUARE WITH 8 DEGREES OF FREEDOM= 15.5118

GENERALIZED POISSON

THE ESTIMATE OF N= 16
THE ESTIMATE OF ALPHA= 0.3152D+00
THE ESTIMATE OF PHI= 0.7183D-01
NUMBER OF ITERATIONS= 7

TAU	OBS	EXPECTED(COND)	SD(COND)
4.00	0	1.80	1.34
5.00	5	1.81	1.35
5.00	0	1.57	1.25
3.00	1	1.24	1.11
2.00	0	1.00	1.00
1.00	2	0.66	0.81
1.00	1	0.59	0.77
1.00	0	0.51	0.72
16.00	2	1.06	1.03
10.00	0	0.77	0.88

THE CUMULATIVE NUMBER OF ERRORS OBSERVED=0.110000D+02

CHI-SQUARE= 15.1733
0.950 QUANTILE FOR CHI-SQUARE WITH 7 DEGREES OF FREEDOM= 14.0702

IBM POISSON

THE ESTIMATE OF PHI=0.443815D-01
NUMBER OF ITERATIONS= 5

THE ESTIMATE OF THE NUMBER OF INITIAL BUGS= 13

TAU	OBS	EXPECTED(COND)	SD(COND)
4.00	0	2.13	1.46
5.00	5	2.40	1.55
5.00	0	1.99	1.41
3.00	1	1.12	1.06
2.00	0	0.68	0.82
1.00	2	0.26	0.51
1.00	1	0.21	0.46
1.00	0	0.17	0.41
16.00	2	1.45	1.20
10.00	0	0.66	0.81

CHI-SQUARE=0.233377D+02
0.950 QUANTILE FOR CHI-SQUARE WITH 8 DEGREES OF FREEDOM= 15.5118

BINOMIAL

THE ESTIMATE OF N= 12
THE ESTIMATE OF A= 0.50630-01

TAU	OBS	EXPECTED(COND)	SD(COND)
4.00	0	2.16	1.47
5.00	5	2.63	1.62
5.00	0	1.51	1.23
3.00	1	0.95	0.98
2.00	0	0.56	0.75
1.00	2	0.28	0.53
1.00	1	0.19	0.43
1.00	0	0.14	0.37
16.00	2	1.54	1.24
10.00	0	0.31	0.55

CHI-SQUARE= 20.8185
0.950 QUANTILE FOR CHI-SQUARE WITH 8 DEGREES OF FREEDOM= 15.5118

IBM POISSON WITH VARIABLE ALPHA

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GLOSSARY

DSLOC	Deliverable Source Lines of Code
IP	Implementation Phase
DVP	Design Verification Phase
CPCI	Computer Program Configuration Item
CPC	Computer Program Component
CU	Compilation Unit
APS	Application Set
DIS	Diagnostic Set
DRS	Data Reduction Set
OSS	Operating System Set
SES	System Exercise Set
SUS	Support Set
SCS	System Control Set
OSV	On-Site Verification
SED	Software Engineering Division
IAW	In Accordance With
OT&E	Operational Test and Evaluation
PTR	Program Trouble Report
PCR	Program Change Report
LAM	List of Affected Modules
PSL	Program Support Library
SCRB	Software Change Review Board
HIPO	Hierarchical Input, Process, Output
FQV	Formal Qualification Verification

APPENDIX B: NEWTON-RAPHSON METHOD

The general technique for solving systems of nonlinear equations employed in this investigation is the Newton-Raphson iterative technique which is described as follows.

Suppose that it is necessary to solve the equation

$$f(X) = 0$$

for X, where f(X) defines a continuously differentiable function at the point X which satisfies f(X) = 0. Define the sequence

$$X_n = X_{n-1} - f(X_{n-1})/f'(X_{n-1})$$

n = 1, 2, ..., where X_0 is an initial guess at X. Then, when X_0 is "close" to X, X_n converges to X as n gets large. The iteration is stopped when successive estimates X_n and X_{n-1} differ by less than a preselected error bound.

When there are two nonlinear equatons and two unknown values, a similar algorithm can be used. Suppose that the following equations must be solved

$$f(X,Y) = 0$$

$$g(X,Y) = 0$$

where f and g possess continuous first partial derivatives at the point (X,Y) which satisfies f(X,Y) = g(X,Y) = 0. Define the sequence

$$X_n = X_{n-1} + \frac{[g(X_{n-1},Y_{n-1})f_2(X_{n-1},Y_{n-1})-f(X_{n-1},Y_{n-1})g_2(X_{n-1},Y_{n-1})]}{D(X_{n-1},Y_{n-1})}$$

$$Y_n = Y_{n-1} + \frac{[g_1(X_{n-1},Y_{n-1})f(X_{n-1},Y_{n-1})-f_1(X_{n-1},Y_{n-1})g(X_{n-1},Y_{n-1})]}{D(X_n-1,Y_{n-1})}$$

where

$$D(X,Y) = f_1(X,Y)g_2(X,Y) - f_2(X,Y)g_1(X,Y),$$

$$f_1\ (X,Y) = \frac{\partial f(X,Y)}{\partial X}\ ,\ f_2\ (X,Y) = \frac{\partial f(X,Y)}{\partial Y}$$

$$g_1(X,Y) = \frac{\partial g(X,Y)}{\partial X}, \quad g_2(X,Y) = \frac{\partial g(X,Y)}{\partial Y}$$

and (X_0, Y_0) is an initial guess at (X, Y). As before, if (X_0, Y_0) is close enough to (X,Y), the sequence (X_n, Y_n) converges to (X,Y) as n becomes larger.

This technique can be generalized to any number of equations and unknowns. Also, derivative approximations can be used in place of exact derivatives; e.g.:

$$\frac{\partial f(X,Y)}{\partial X} \approx \frac{f(X+h,Y) - f(X-h,Y)}{2h}$$

where h is small.

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